

THREE ESSAYS IN APPLIED INDUSTRIAL ORGANIZATION

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THREE ESSAYS IN APPLIED INDUSTRIAL ORGANIZATION

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To my parents. This is my small contribution to bringing a smile to their faces after
they raised me.

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SUMMARY

In this dissertation I analyze the impact of factors such as competition, technology and consumer behavior on the pricing and quality decisions of firms and service providers, as well as how certain pricing strategies can lead to unintended effects.

In Chapter 1, I show three results pertaining to a firm selling to buyers who focus more on the salient attribute of a product relative to other attributes. First, the firm can make more profit by making quality salient (i.e. make the buyer focus on quality, not price). Second, whether the firm can make quality the salient attribute to the buyers depends on the firm's cost of upgrading quality and consumers' preferences for quality upgrades. Third, the firm can profitably deviate from the optimal price-discriminating menu of price and quality by granting an additional discount to consumers who value quality more or by downgrading quality of the low-quality good.

In Chapter 2, using data on Uber and Lyft trips and complaints against taxi drivers, I show that increased competition from Uber has led to more complaints regarding unsafe driving, refused pick-ups etc. by taxi drivers, which is opposite to what one would expect.

Finally, in Chapter 3, I show three new unintended effects of price-matching. First, a price-match guarantee may decrease firms' incentives to invest in reducing costs. Second, it may reduce the incentive to invest in enhancing quality. Third, without price-matching, low-cost firms produce too little relative to the social optimum and I show that price-matching can aggravate this problem by allowing high-cost firms to steal further market share.

CHAPTER 1

PRICE DISCRIMINATION AND SALIENCE

1.1 Introduction

In this paper, I combine the standard vertical differentiation model and the model of salience to analyze the price and quality decisions of a monopolist facing consumers who are “salient” thinkers, both when it can and when it cannot identify buyer types. Often decision-makers focus too much on one attribute relative to the other attributes that make up the choice context. In the case of choosing a price-quality pair, Bordalo *et al.* (2015a) show that while standard¹ thinkers focus equally on price and quality, the two attributes in this choice context, salient thinkers will overweight quality or price depending on whichever is salient. As a result of over-weighting price or quality, salient buyers choices differ from those of standard buyers. This in turn can affect the menu of quality-price pairs the firm will offer.

It is important for such a firm to understand whether price or quality should be made salient to the buyer in order to maximize profits. Furthermore, it is important to understand how price discrimination helps or hinders inducing such salience (price- or quality-salience, whichever is more profitable) and vice versa. In other words, the twin goals of discriminating on price and inducing salience can interact, which can result in significantly different outcomes in equilibrium. I provide the first systematic analysis of these differences.

With both types of price discrimination, I show that the monopolist prefers to make quality salient in the eyes of the consumer. Then for each case I show what

¹I use the word ‘standard’ to refer to consumers as described in the traditional Econ literature who do not display any non-standard behavior due to irrationality or bounded rationality or something else.

determines whether it will succeed in making quality salient or not. The answer depends on consumer preferences for quality and the cost of upgrading quality and the type of price discrimination it can engage in.

In the case of first-degree price discrimination, price is salient when the cost of improving quality is convex. However, neither price nor quality is salient when cost is linear. The reason for this is that the monopolist is able to fully transfer to the buyer any cost of increasing quality when it can identify buyer types. With linear cost, doubling the quality leads to doubling the cost and hence price. Hence, quality and price ratios are the same for all products sold by the firm, leading to no feature becoming salient in the eyes of the buyer. However, with convex cost, doubling the quality leads to more than double the increase in cost and price, raising the ratio of prices relative to that of quality, which lead to price-salience. I then show that with linear cost, the monopolist can increase profits by inducing quality salience by selling the high-quality good at a discount, something that it would not do with standard buyers.

When the monopolist cannot distinguish between buyer types, the information rent and downward distortion in quality from second-degree price discrimination changes the outcomes in terms of salience. Moreover, both the shape of the cost function *and* that of the utility function now play a role. While price remains salient with sufficiently convex costs, quality can become salient by default when utility for quality is concave enough. In the case of linear costs, while neither price nor quality is salient in the first-degree case, the standard discount given to the high-type buyer and the degradation in quality of the low-quality good under second-degree price discrimination means that the prices of the two goods move closer and the qualities move farther apart, resulting in quality-salience.

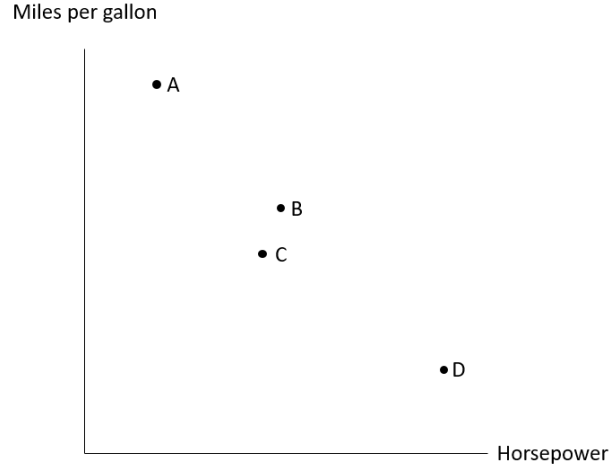


Figure 1.1: Attraction Effect, Compromise Effect and Similarity Effect

1.2 Related literature

Papers such as Gabaix and Laibson (2006) and DellaVigna and Malmendier (2006) document systematic deviations of consumers from standard behavior and model firm strategy exploiting such behavior. This paper contributes to this growing literature on what is now called “behavioral industrial organization”² by showing a specific instance of how a firm exploits salient behavior by consumers.

Preferences affected by salient thinking is one manifestation of reference-dependent or context-dependent preferences. Huber *et al.* (1982) consider adding a product to a buyer’s choice set of two existing products A and B. I portray this in Figure 1 using two attributes of several car models – miles per gallon (mpg) and horsepower. This new item C is clearly inferior to one of the original alternatives but not the other, i.e. car C has less horsepower and mpg than car B. The presence of this new alternative, a “decoy” good, increases the attractiveness of the now “asymmetrically dominating” alternative.³. They name this the “attraction effect”. Simonson (1989) builds on this

²See Ellison (2006), Spiegler (2011) and Eliaz and Spiegler (2015) for detailed literature reviews and book-length treatments on Behavioral Industrial Organization.

³For an actual example, see (Ariely, 2008) The author points out how the *The Economist* newspaper had three subscription offers – print, digital and print+digital. The latter two were the same price. In an experiment, a higher fraction of MBA students chose the print+digital when the

by introducing the “compromise effect”. An alternative’s choice probability increases when it becomes a compromise or middle alternative, even if there is no superiority relationship; adding D in Figure 1 increases the market share of B relative to A because B is now a compromise between A and D.⁴ The “similarity effect” says D should steal more share from B rather than A because of higher substitutability between B and D. A similar inconsistency is that of “choice overload”. When offered *more* choices, customers’ likelihood of buying any one of the items *decreases* (Iyengar and Lepper, 2000).

All of the above effects violate the assumption of “independence of irrelevant alternatives”. standard buyers will always buy the item that maximizes their utility regardless of the presence of alternatives in his choice set. The existence of these violations led to attempts to explain such behavior. While these attempts have diverged on significant details, the common theme is that preferences are context-dependent. An early paper modeling context-dependent preferences is by Tversky and Simonson (1993). More recently, Kamenica (2008) tries to explain the compromise effect and Cunningham (2011) models being exposed to a larger value along some dimension that makes a person less sensitive to marginal differences along that dimension. Kőszegi and Szeidl (2012)’s “focusing” model states that a person focuses more on attributes in which her options differ more. Bushong *et al.* (2015)’s “relative thinking” model on the other hand states that a person weighs a given change along a consumption dimension by less when it is compared to larger changes along that dimension. Azar (2007) builds a similar model of relative thinking.

As I elaborate in Section 1.3.1, these papers are essentially trying to capture two features of human sensory perception – one that is prone to notice bigger differences vs. those that are small, and the other that is less capable of noticing big differences when all items in a context are bigger. While models on focusing, relative thinking

digital-only option was offered alongside it, compared to when it wasn’t.

⁴This figure is a modified version of Figure B from Simonson (1989).

etc. capture one of these two features or the other but not both at the same time, Bordalo, Gennaioli and Schleifer, in a series of papers, build a model of “salient thinking” that incorporate both.⁵

Bordalo *et al.* (2012) attempt to explain the Allais paradox, preference reversals and other puzzling behavior of decisions makers choosing under risk using the theory of salience. For example, adding a lottery that is clearly dominated by another lottery already in the choice set makes the riskiness of the dominating lottery less salient leading to preference reversals. Bordalo *et al.* (2013) apply salience to consumer decision-making.

Bordalo *et al.* (2015b) analyzes judicial decisions through the lens of salience theory. They demonstrate that judges or parties to a lawsuit may overweight salient aspects of a case, some of which may be legally irrelevant. For instance, the presence of a dominated settlement offer increases the salience of the dominating offer and leads to a higher probability of acceptance by the salient plaintiff, relative to the standard plaintiff.

Bordalo *et al.* (2015a) is perhaps the closest to my paper, where they analyze price and quality choices by firms in a duopoly setting. They produce a result that is similar to mine – the cost-to-quality ratio determines whether price or quality is salient. What they didn’t consider was the issue of price discrimination. They also did not study the interaction between how consumers value quality and the cost structure. My analysis in this paper closes these gaps.

Several theoretical and empirical papers on salience since the papers by Bordalo, Gennaioli and Schleifer has further established the importance of salient thinking.⁶ Herweg *et al.* (2017) show that a dominant firm facing competition from a competitive

⁵The word “salience” was first used to refer to such thinking by Taylor and Thompson (1982) who state that “...salience refers to the phenomenon that when ones attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments.”

⁶See a detailed review by Herweg *et al.* (2018).

fringe can use a decoy good to make it's own good's quality salient while at the same time make the price of the competitive fringe's good salient, thereby increasing profits.

Helfrich and Herweg (2017) attempt to explain why some brand manufacturers impose restrictions on retailers regarding selling their high-quality products online. They posit that the online marketplace is prone to more aggressive price competition and hence a high price is salient to consumers buying online. Not allowing the retailer to sell online allows the manufacturer to incentivize the retailer to invest in making quality salient in offline sales.

Dertwinkel-Kalt (2016) consider health campaigns by the government and firms. They show that two health campaigns, one promoting a healthy product and one demoting an unhealthy product has asymmetric affects, with the latter being more effective in reducing consumption of the unhealthy product. This is based on his assumption that consumers are more familiar with the unhealthy product due to them using it (and hence the need for the campaign to induce switching) and as a result they overweight (negative) information on the unhealthy product more. Such information is salient in their decision-making.

Early empirical evidence supporting salient thinking comes from Chetty *et al.* (2009). Using a field experiment in a grocery store, they find that when tax is included in posted prices, consumers buy 8% less than if tax was not posted but only charged at time of purchase. By posting the tax along with the price, the store made the tax salient. standard buyers would not fail to factor in the tax.

Hastings and Shapiro (2013) study uniform price hikes of all grades of gasoline and find more switching to lower grades than income-effects can explain. Bordalo *et al.* (2013) argues that this is because a parallel increase in price of all grades make the price of the high-quality gas to be salient, making the buyer more price-sensitive. Dertwinkel-Kalt *et al.* (2017) uses a lab experiment on choice of internet services and find similar results.

Aside from reference-dependent preferences and salience, the results in this paper also add to the literature on price discrimination in the presence of consumers with non-standard preferences, such as Carbajal and Ely (2016) who analyze price discrimination when consumers are loss-averse and find downward distortion beyond the standard distortion in Mussa and Rosen (1978). In this paper, I show a distortion in prices in the first-degree price-discrimination case with salient consumers while there is no such distortion with standard buyers.

Armstrong (2016) shows how results that apply to quantity discounts and non-linear pricing in general can be re-interpreted in the context of quality instead of quantity.⁷ While the literature on vertical differentiation tends to use linear utility for analysis, I consider both linear and non-linear utility and show that non-linearity can impact which product feature becomes salient. Such non-linearity in utility leading to non-linear pricing results not in quantity discounts but rather discounts for higher units of quality.

The rest of the paper is as follows. I describe the necessary components of the theory of salience in Section 1.3.1 to facilitate the analysis that follows. In Section 1.3.2, I describe the model of vertical differentiation I use for the rest of the paper. Exogenous and endogenous quality are analyzed in Sections 1.4 and 1.5 respectively. I discuss whether price- or quality-salience is more profitable in Section 1.6 and how to induce the more profitable kind of salience. I conclude in Section 2.7.

1.3 Model

1.3.1 Salience Theory

Human sensory perception tend to display two features. First, they are designed to detect variations in stimuli. In a small town with one tall building, we notice that

⁷Belleflamme and Peitz (2015) does the reverse by introducing the Mussa-Rosen quality model first and re-interprets it to analyze quantity discounts.

building before we notice the other buildings, i.e. the tall building is more “salient”. Second, human senses are less sensitive to increasing changes in stimuli. So in a large city with many skyscrapers, the tallest of them stand out less in our eyes. In other words, the salience of the tallest building decreases with uniform increases in height of *all* buildings. A salience function (Bordalo *et al.*, 2013) captures both of these two features:

1. *Ordering*: For any $x, x', y, y' \in \mathbb{R}_{\geq 0}$ with $[x, y] \subset [x', y']$, then $\sigma(x, y) < \sigma(x', y')$.
2. *Diminishing sensitivity*: For all $x, y \in \mathbb{R}_{\geq 0}$ and $\alpha > 0$, it holds that $\sigma(\alpha + x, \alpha + y) < \sigma(x, y)$.

The “ordering” property states that the difference between two features is more noticeable when they are farther apart. Continuing with the example of tall buildings, a 10-story building will stand out more when all the other buildings are 2-stories because there is a difference of 8 floors between it and the rest whereas any individual 2-story building does not differ from the remaining 2-story buildings at all and hence does not stand out. The “diminishing sensitivity” property implies that a 50-story building will be less salient when all the other buildings are 42-stories, relative to the previous example of 10 and 2-story buildings despite the fact that the difference is 8 floors in both cases.

Note that an increase in the number of floors of the tallest building increases the salience of that building (ordering effect) but also increases the average height of all buildings thereby decreasing salience (diminishing sensitivity effect). So a function that captures salience should incorporate this trade-off. Ensuring that the salience function satisfies ordering and homogeneity of degree 0 successfully achieves that. This is because together with ordering, homogeneity of degree 0 implies diminishing sensitivity.⁸

⁸In fact, homogeneity of degree 0 is a stronger condition than diminishing sensitivity. For more

Homogeneity of degree 0 implies $\sigma(\alpha \cdot a_k, \alpha \cdot \bar{a}) = \sigma(a_k, \bar{a})$, that is, scaling up or down all the values in a set does not affect the salience of any one of them. More importantly, a salience function with the homogeneity of degree 0 property captures the trade-off between ordering and diminishing sensitivity by ensuring that the former dominates the latter if and only if the change in an attribute a_k of element k is greater than the resulting change in the attribute average \bar{a} in that set and vice versa.

To proceed with the analysis of price and quality choice by a firm facing salient consumers, let a consumer choose from a set of goods called the “consideration set” $\mathcal{C} \equiv \{(q_k, p_k)\}_{k=1, \dots, N}$ with each good k having price p_k and quality q_k . The “reference good” in \mathcal{C} is the good with the average price \bar{p} and average quality \bar{q} . Then, Bordalo *et al.* (2013) prove the following result:

Lemma 1. *If the consumers’ salience function is homogeneous of degree 0, and goods k , L and H do not dominate nor are dominated by the reference good, then*

- (i) *The higher quality or lower price of good k is salient iff $\frac{q_k}{\bar{q}} > \frac{p_k}{\bar{p}}$, whereas the higher price or lower quality of good k is salient iff $\frac{q_k}{\bar{q}} < \frac{p_k}{\bar{p}}$.*
- (ii) *In the case of two goods H (high-quality) and L (low-quality), quality is salient for both goods if $\frac{q_H}{q_L} > \frac{p_H}{p_L}$, whereas price is salient for both goods if $\frac{p_H}{p_L} > \frac{q_H}{q_L}$.*

To see why this is true, note that due to homogeneity of degree 0, the salience of good k ’s quality $\sigma(q_k, \bar{q})$ and price $\sigma(p_k, \bar{p})$ can be expressed as $\sigma(\frac{q_k}{\bar{q}}, 1)$ and $\sigma(\frac{p_k}{\bar{p}}, 1)$ respectively, where both $\frac{q_k}{\bar{q}}$ and $\frac{p_k}{\bar{p}}$ are larger than one. The ordering property then implies that the high quality of good k is salient if and only if $\frac{q_k}{\bar{q}} > \frac{p_k}{\bar{p}}$. The steps to show that $\frac{q_H}{q_L} > \frac{p_H}{p_L}$ implies $\frac{q_H}{q_L} > \frac{p_H}{p_L}$ is in the Appendix.

Note that while quality of good k alone is salient in the N good case and we do not know about the salience of price or quality of the other goods without further

about the relationship between ordering, homogeneity of degree 0 and diminishing sensitivity, see Footnote 3 of Bordalo *et al.* (2013). They show that most of the predictions of salience theory hold with this stricter assumption.

information, quality (or price) is salient for *both* goods in the two-good case. To understand why, consider the case of quality-salience. $\frac{q_H}{q_L} > \frac{p_H}{p_L}$ implies $\frac{q_L}{q} < \frac{p_L}{p}$ and hence the *lower* quality of Good L is salient at the same time when the *higher* quality of Good H is salient. So while the consumer overvalues both goods, he/she overvalues the high-quality good more.

Lemma 1 provides the key result that will allow us to determine when quality becomes salient and when price becomes salient, given specific consumer preferences and technology of quality upgrades. In particular, it implies quality will be salient in the eyes of the buyer when the ratio of qualities of two goods is greater than their price-ratio whereas price will be salient if the price-ratio is larger. Note that this effectively translates to salient thinkers focusing on the attribute whose features show bigger (relative) differences than attributes whose features show smaller (relative) differences. For instance the requirement of quality-salience, that the quality-ratio must be higher, can be rewritten as

$$\begin{aligned}\frac{q_H}{q_L} &> \frac{p_H}{p_L} \\ \frac{q_H}{q_L} - 1 &> \frac{p_H}{p_L} - 1 \\ \frac{q_H - q_L}{q_L} &> \frac{p_H - p_L}{p_L} \\ \% \Delta q &> \% \Delta p\end{aligned}$$

which means that buyers will focus on the the qualities of two products if the percentage difference in quality among the two items is greater than the percentage gap in prices. If a buyer is choosing between Printer A priced at \$100 and Printer B priced at \$120 and the printing speeds are 100 pages per minute (ppm) and 150 ppm respectively, then the price gap is 20% and the quality gap (quality here being the printing speed) is 50%. Thus, the buyer's attention will be more on the printing speed

and less on price.⁹

It is worth pointing out that there can be several ways a feature of a product can become salient in the eyes of the buyer. The specific reason of percentage differences in price vs. quality causing salience of one or the other, is just one such mechanism. Another way may be the way the price and quality information is presented to the buyer such as the font size and color of the writing. Similarly, quality may be the focus of consumers in Starbucks and price the focus in Walmart regardless of price vs. quality differences between products because of store decorations or marketing slogans that aim to induce buyers to focus on price vs. quality. Having recognized such alternative means through which salience of particular attributes can arise, I now proceed with the definition of salience as used by BGS and others in the Salience literature and defined above in Lemma 1.

To incorporate salience into the utility function of consumers, I use the following class of utility functions, which is a modified version of the utility function used in Bordalo *et al.* (2015a):

$$u_k^S(\theta, q_k, p_k, \delta) = \Delta u(\theta, q_k) - p_k \quad (1.1)$$

where

$$\Delta = \begin{cases} \frac{1}{\delta} & \text{if } \sigma(q_k, \bar{q}) > \sigma(p_k, \bar{p}) \\ \delta & \text{if } \sigma(q_k, \bar{q}) < \sigma(p_k, \bar{p}) \\ 1 & \text{if } \sigma(q_k, \bar{q}) = \sigma(p_k, \bar{p}) \end{cases}$$

and $0 < \delta \leq 1$ is the degree of salience. $\delta = 1$ implies “standard” consumer behavior whereas a consumer approaches full salience as $\delta \rightarrow 0$. When quality is salient, it is *overweighted* by the factor $\frac{1}{\delta}$. If price is salient on the other hand, quality is *underweighted* by the factor δ relative to price, which is just a monotonic transfor-

⁹The quality ratio is 1.25 and the price ratio is 1 in this case. As the quality-ratio is greater, we reach the same conclusion of quality-salience in two alternative but similar ways.

mation of the utility function $u(\theta, q) - \frac{1}{\delta}p$ where price is overweighted. In contrast, standard buyers do not overweight either attribute and hence has the utility function $u(\theta, q) - p$ regardless of which attribute is salient.

$\theta \in [0, 1]$ is the taste parameter for quality that varies across consumers. A higher θ indicates a higher valuation for quality. $q \geq 0$ and $p \geq 0$ are quality and price of the good respectively. I make the following assumption for the above class of functions:

Assumption 1. *u^S is based on a salience function that satisfies ordering and homogeneity of degree 0.*

I also assume throughout the paper that δ is exogenous and homogeneous across consumers.

1.3.2 Vertical Differentiation

I use the standard vertical differentiation model with two types of consumers. A monopolist sells two products, high-quality good H and low-quality good L , to two groups of consumers with differing taste parameters – fraction λ of “high-type” buyers with taste parameter θ_H and fraction $1 - \lambda$ of “low-type” buyers with taste parameter θ_L . I assume $\theta_H > \theta_L$ i.e. high-type buyer values a given quality more than low-type. The total mass of consumers is normalized to 1.

To keep the analysis tractable, I assume simple functional forms for utility and cost. The utility function

$$U(\theta, q) = \Delta\theta q^b - p \tag{1.2}$$

may be linear for $b = 1$ or concave $U(\theta, q) = \Delta\theta q^b - p$ for $0 < b < 1$ or convex for $b > 1$. Each buyer buys either one unit of H or one unit of L, or neither.

On the firm side, if quality is endogenous, marginal cost of an additional unit of quality

$$C(q) = cq^a \tag{1.3}$$

is made up of two components. c captures the component that is independent of quality, i.e. it is the fixed marginal cost of producing one more unit. q^a captures the variable component that changes with quality. $C(q)$ may be linear in quality for $a = 1$ or convex for $a > 1$ or concave for $a < 1$.¹⁰ If quality is exogenous however, let $C(q_H) = c_H$ and $C(q_L) = c_L$.

To motivate the use of linear and concave preferences for quality, I present a couple of examples. Car tires usually have mileage ratings to indicate the number of miles of use the buyer may expect from them. Higher ratings is higher quality in this context. It is reasonable to claim that, *ceteris paribus*, the buyer will value a tire with a rating of 50,000 miles twice as much as a tire with a rating of 25,000 miles. In other words, utility is approximately linear over the relevant quality range.

In contrast, there are diminishing returns in utility to have faster microprocessors in computers, smartphones etc., speed being the measure of quality in this case. This is because a processor that is twice as fast in clock speed relative to another processor will not double the speed of completing tasks on a computer unless other components such as RAM and hard drive are also upgraded to prevent bottlenecks. Further, except advanced users, users do not always get to fully utilize the additional speed for everyday tasks.

Now consider linear and convex costs of upgrading quality. If the duration of a battery is proportional to the number of cells it has inside and if the marginal cost of each cell is constant, then a battery that lasts twice as long would cost twice as much and would reflect a linear cost function.

On the other hand, steel and carbon fiber used in production of bikes¹¹ and cars provide a good example of convex costs. While the production of steel is heavily

¹⁰While cases of convex utility and concave costs may be uncommon, I am keeping the analysis general to accommodate such (unlikely) possibilities.

¹¹I mean here cycles and not motorbikes. While carbon fiber bikes are very common, this is not yet the case for motorbikes.

automated, production of carbon fiber requires significant labor.¹² Heavier cars are less fuel-efficient and heavier bikes are slower and hence the weight of the item is the dimension of quality in this context. While a bike made of carbon fiber may be 50% lighter than a steel bike, it is usually a lot more than 50% more expensive to produce than the steel bike. Similar observations can be made regarding regular cars made of steel and sports cars with carbon fiber components.

While the specific examples I use here may or may not reflect the true functional forms that match cost data and consumer behavior, the important thing is to realize there are differences in production technology and how consumers value additional quality across different products and services.

Given the utility and cost functions, the monopolist maximizes the following profit function:

$$\max_{\{q_H, q_L, p_H, p_L\}} \pi = \lambda(p - cq_H^a) + (1 - \lambda)(p - cq_L^a) \quad (1.4)$$

subject to the following participation and incentive compatibility constraints

$$\Delta\theta_L q_L^b - p_L \geq 0 \quad \text{PC for low-type}$$

$$\Delta\theta_H q_H^b - p_H \geq 0 \quad \text{PC for high-type}$$

$$\Delta\theta_L q_L^b - p_L \geq \Delta\theta_L q_H^b - p_H \quad \text{IC for low-type}$$

$$\Delta\theta_H q_H^b - p_H \geq \Delta\theta_H q_L^b - p_L \quad \text{IC for high-type}$$

The subset of constraints that will bind in a given situation will depend on whether the monopolist can or cannot observe consumer type.

¹²See for example Swaby, R. (2011, September 23) Why is Carbon Fiber So Expensive? *Gizmodo*. Retrieved from <https://gizmodo.com/5843276/why-is-carbon-fiber-so-expensive>

1.4 Exogenous Quality

I begin with the less complicated case of exogenous quality. This may either be because the firm is making decisions in the short-run and can only change price or because of some regulation requiring quality to be at a certain level or some other reason. The monopolist maximizes

$$\max_{p_H, p_L} \pi = \lambda(\Delta p_H - c_H) + (1 - \lambda)(\Delta p_L - c_L) \quad (1.5)$$

where $c_H > c_L$ are the exogenous per-unit cost of producing the high- and low-quality goods respectively.

1.4.1 First Degree Price Discrimination

I first consider the case of two types of buyers and the monopolist can identify their types and hence engages in first-degree price discrimination (FD). Incentive-compatibility constraints are irrelevant, and from the binding participation constraints, we have

$$p_L = \Delta\theta_L q_L^b \quad \text{and} \quad p_H = \Delta\theta_H q_H^b \quad (1.6)$$

where q_H and q_L are fixed. The price ratio is then

$$\frac{p_H}{p_L} = \frac{\theta_H}{\theta_L} \left(\frac{q_H}{q_L} \right)^b \quad (1.7)$$

Given $\theta_H > \theta_L$, we note immediately that the price ratio is greater than the quality ratio if utility is linear in quality upgrades ($b = 1$), and hence price is salient. In general, quality will be salient only if the utility function is sufficiently concave

$$b < 1 - \frac{\ln\theta_H - \ln\theta_L}{\ln q_H - \ln q_L} \equiv \bar{b}^{FD} \quad (1.8)$$

The reason is as follows. Strongly diminishing utility to improvements in quality (low value of b) limits the firm's ability to charge a price for the high-quality good that is much higher than that of the low-quality good. This results in a large quality gap between the two goods but not as large a price gap, leading to quality-salience.

To ensure positive profits, optimal prices charged must be greater than the cost of the products. These necessary conditions are $p_H = \theta_H q_H^b > c_H$ and $p_L = \theta_L q_L^b > c_L$ which lead to the condition

$$b > \max \left\{ \frac{\ln c_L - \ln \theta_L}{\ln q_L}, \frac{\ln c_H - \ln \theta_H}{\ln q_H} \right\} \equiv \underline{b}^{FD} \quad (1.9)$$

This implies that diminishing utility to higher quality cannot be so rapid that it prevents the firm from profitably selling the two goods. In such a case, it would result in a pooling equilibrium with the firm selling either the high- or low-quality good alone to both customers.

It should be noted here that the parameter a capturing the shape of the cost-upgrade function plays no role in this analysis for obvious reasons. Because quality is exogenous, the only that thing matters from the cost perspective is the ratio $\frac{c_H}{c_L}$ which has an impact on the lower bound of b as can be seen above.

1.4.2 Second Degree Price Discrimination

If the monopolist cannot identify buyers types and hence engages in second-degree price discrimination, we know from the standard principal-agent model with hidden information (Laffont and Martimort, 2009) that only the participation constraint for the low-type and incentive compatibility constraint for the high-type bind. Hence we have

$$p_L = \Delta \theta_L q_L^b \quad \text{and} \quad p_H = \Delta(\theta_H q_H^b - (\theta_H - \theta_L) q_L^b) \quad (1.10)$$

The price ratio is

$$\frac{p_H}{p_L} = \frac{\theta_H q_H^b - (\theta_H - \theta_L) q_L^b}{\theta_L q_L^b} \quad (1.11)$$

Price is salient if

$$\frac{\theta_H q_H^b - (\theta_H - \theta_L) q_L^b}{\theta_L q_L^b} > \frac{q_H}{q_L} \iff \left(\frac{\theta_H - \theta_L}{\theta_H} \right)^{\frac{1}{b}} < \frac{q_H}{q_L} \quad (1.12)$$

For the linear case $b = 1$, it can be easily shown that the LHS of (1.12) is greater, i.e. price is salient. In general, quality will be salient only if the utility function is sufficiently concave

$$b < \frac{\ln \theta_H - \ln(\theta_H - \theta_L)}{\ln q_H - \ln q_L} \equiv \bar{b}^{SD}$$

The intuition for this condition is similar to that in the first-degree case. Sufficient conditions¹³ for profitability in the second-degree case lead to the condition

$$b > \max \left\{ \frac{\ln c_L - \ln \theta_L}{\ln q_L}, \frac{\ln c_H - \ln \theta_L}{\ln q_H} \right\} \equiv \underline{b}^{SD}$$

The results for the exogenous quality cases are summarized in the following proposition:

Proposition 1. *With exogenous quality and the*

- (i) *ability to identify buyer types, quality is salient if $\underline{b}^{FD} < b < \bar{b}^{FD}$. For $b > \bar{b}^{FD}$, price is salient.*
- (ii) *inability to identify buyer types, quality is salient if $\underline{b}^{SD} < b < \bar{b}^{SD}$. For $b > \bar{b}^{SD}$, price is salient.*

¹³The more complicated expressions of prices and qualities under second-degree price discrimination make it less tractable to generate necessary conditions similar to those found for the case of first-degree price discrimination. Hence I suffice with sufficient conditions.

1.5 Endogenous Quality

1.5.1 First Degree Price Discrimination

The maximization problem becomes

$$\max_{\{q_H, q_L\}} \pi^{FD} = \lambda(\Delta\theta_H q_H^b - c q_H^a) + (1 - \lambda)(\Delta\theta_L q_L^b - c q_L^a) \quad (1.13)$$

which gives

$$q_i^{FD} = \left(\frac{b}{ac}\Delta\theta_i\right)^{\frac{1}{a-b}} \quad \text{and} \quad p_i^{FD} = \Delta\theta_i \left(\frac{b}{ac}\Delta\theta_i\right)^{\frac{b}{a-b}} \quad i = L, H \quad (1.14)$$

The price- and quality-ratios are, respectively,

$$\frac{p^H}{p^L} = \frac{\theta_H}{\theta_L} \left(\frac{\theta_H}{\theta_L}\right)^{\frac{b}{a-b}} = \left(\frac{\theta_H}{\theta_L}\right)^{\frac{a}{a-b}} \quad \text{and} \quad \frac{q^H}{q^L} = \left(\frac{\theta_H}{\theta_L}\right)^{\frac{1}{a-b}} \quad (1.15)$$

To ensure $p_H > p_L$ and $q_H > q_L$,¹⁴ we must have:

Assumption 2. $a > b$, i.e. the cost function is more convex (or less concave) than the utility function.

Price is salient when the price-ratio is greater than the quality-ratio:

$$\left(\frac{\theta_H}{\theta_L}\right)^{\frac{a}{a-b}} > \left(\frac{\theta_H}{\theta_L}\right)^{\frac{1}{a-b}} \iff a > 1 \quad (1.16)$$

For $a = 1$, i.e. linear costs, neither price nor quality is salient (or equivalently, price and quality are *equally* salient). I summarize the results in the following proposition:

Proposition 2. *With endogenous quality and first-degree price discrimination,*

(i) *price is salient if cost of upgrading quality is convex,*

¹⁴The second-order conditions require the same assumption. See Appendix 1.8.3.

(ii) *neither price nor quality is salient when cost is linear,*

(iii) *quality is salient if cost is concave.*

The intuition for this is straightforward. Because the monopolist can distinguish between buyer types, it passes on all costs of upgrading quality to them. When cost of upgrading quality is linear, price rises proportionally with quality. If for instance the high-quality good is twice as superior in quality than the low-quality good, the price of the former will also be twice as much. This leads to the same price-quality ratios for both goods. Indeed this result can be easily extended for the n -buyer n -good case as long as first-degree price discrimination is feasible.

If on the other hand cost is convex, doubling the quality will entail incurring more than double the cost and hence more than double the price. This then leads to a lower quality-per-dollar for the high-quality good and hence price becomes salient.

1.5.2 Second Degree Price Discrimination

Using the participation constraint for the low-type and incentive compatibility constraint for the high-type, we have

$$p_L = \Delta\theta_L q_L^b \quad \text{and} \quad p_H = \Delta(\theta_H q_H^b - (\theta_H - \theta_L)q_L^b)$$

The maximization problem becomes

$$\max_{\{q_H, q_L\}} \pi^{SD} = \lambda(\Delta(\theta_H q_H^b - (\theta_H - \theta_L)q_L^b) - cq_H^a) + (1 - \lambda)(\Delta\theta_L q_L^b - cq_L^a) \quad (1.17)$$

which leads to optimal qualities:

$$q_L^{SD} = \left(\frac{\Delta b}{ac}\Theta\right)^{\frac{1}{a-b}} \quad \text{and} \quad q_H^{SD} = \left(\frac{\Delta b}{ac}\theta_H\right)^{\frac{1}{a-b}} \quad (1.18)$$

and optimal prices:

$$p_L^{SD} = \Delta^{\frac{a}{a-b}} \theta_L \left(\frac{b}{ac} \Theta \right)^{\frac{b}{a-b}} \text{ and } p_H^{SD} = \Delta^{\frac{a}{a-b}} \left(\theta_H^{\frac{a}{a-b}} \left(\frac{b}{ac} \right)^{\frac{b}{a-b}} - (\theta_H - \theta_L) \left[\frac{b}{ac} \Theta \right]^{\frac{b}{a-b}} \right) \quad (1.19)$$

where $\Theta = \theta_L - \frac{\lambda}{1-\lambda}(\theta_H - \theta_L)$.

To ensure positive price and quality for the low-quality good, we must have $\Theta > 0$ or $\lambda < \frac{\theta_L}{\theta_H}$. Hence I make the following assumption:

Assumption 3. $\lambda < \frac{\theta_L}{\theta_H}$. *The fraction of high-types is sufficiently low.*¹⁵

This is what Mussa and Rosen (1978) pointed out – that a sufficiently high fraction of high-types will squeeze out the low-types from the market. The monopolist can reduce the information rent it gives to the high-type by lowering the quality of the good bought by the low-type. This downward distortion in quality of the low-quality good deters the high-type from buying it and relaxes the need for the monopolist to lower the price of the high-quality good. Higher the fraction of high-types vis-a-vis low-types, greater the impact of such downward distortion in the quality of the low-quality good on reducing the information rent for the high-types. A sufficiently high fraction of high-types drives the quality of the low-quality good to zero. In other words, the monopolist sells the high-quality good only. An alternative way to express Assumption 3 is that, given a fraction of high-type customers, the taste parameter for the low-type must be sufficiently close to that of the high-type $\theta_L > \lambda \theta_H$. If the low-type values quality much less than the high-type, it will not be profitable to cater to them while persuading the high-type to not buy the low-quality good.

What is important in this paper's context is that salience is relevant only in situations of more than one good. By definition of salience discussed above, the quality or price of a good stands out in the eyes of the buyer when contrasted with that of the “reference” good. But with only one good in the consumer's choice set,

¹⁵Again, second-order conditions require this also. See Appendix 1.8.3.

the high-quality good is the reference good itself, and hence the need for Assumption 3 to ensure that the monopolist sells two goods.

Given optimal prices and qualities above, the quality-ratio is larger than the price-ratio if (after simplifying both ratios):

$$\left(\frac{\Theta^{1-b}}{\theta_H^{1-a}}\right)^{\frac{1}{a-b}} - (\theta_H - \theta_L) \left(\frac{\Theta}{\theta_H}\right)^{\frac{1}{a-b}} < \theta_L \quad (1.20)$$

Unlike in the first-degree case, the parameter b capturing the shape of the utility function does play a role. We will consider two general cases. First if $a - b \rightarrow \infty$, i.e. the cost function is sufficiently convex (which can be alternatively expressed as $a \rightarrow \infty$ for a given b), then the inequality in (1.20) at the limit becomes

$$\left(\frac{\Theta^{1-b}}{\theta_H^{1-a}}\right)^0 - (\theta_H - \theta_L) \left(\frac{\Theta}{\theta_H}\right)^0 < \theta_L \iff 1 < \theta_H$$

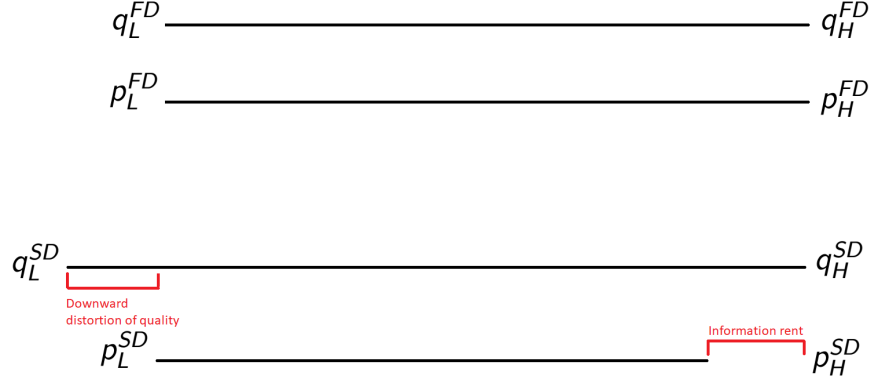
which is not true. Hence price is salient when the cost function is sufficiently convex, regardless of the value of b . Next, consider when $b \rightarrow 0$. At the limit, the inequality becomes

$$\left(\frac{\Theta}{\theta_H^{1-a}}\right)^{\frac{1}{a}} - (\theta_H - \theta_L) \left(\frac{\Theta}{\theta_H}\right)^{\frac{1}{a}} < \theta_L \iff \Theta < \theta_H$$

which is true since $\Theta < \theta_L < \theta_H$. Thus, quality is salient if the utility function is sufficiently concave. From the above two cases, we can see that there is a tug-of-war between convexity of cost and concavity of utility. While increasing convexity in cost of upgrading quality pushes prices of the two goods farther apart and hence pulls towards price-salience, diminishing returns to quality squeezes prices closer together and thus pulls towards quality-salience.

Recall that under first-degree price discrimination and linear cost, neither price nor quality is salient. To contrast with second-degree price discrimination, consider

Figure 1.2: Quality-salience in second-degree price discrimination



the case of linear cost, $a = 1$, under second-degree price discrimination:

$$\left(\frac{\Theta^{1-b}}{\theta_H^0} \right)^{\frac{1}{1-b}} - (\theta_H - \theta_L) \left(\frac{\Theta}{\theta_H} \right)^{\frac{1}{1-b}} < \theta_L \iff \Theta - \theta_L < (\theta_H - \theta_L) \left(\frac{\Theta}{\theta_H} \right)^{\frac{1}{1-b}}$$

which holds because the LHS is negative and both terms of the RHS are positive. Therefore, quality is salient unlike in the first-degree case. Figure 1.2 provides the intuition for this contrast in results between the first- and second-degree cases. Two things that result from the monopolist's desire to screen high-types from low-types is the information rent given to the high-type and the downward distortion in quality of the low-quality good. So, when cost of upgrading quality is linear resulting in equality price- and quality-ratios under first-degree price discrimination case (as seen in the top part of Figure 1.2), the information rent decreases the gap between the two prices while the downward distortion increases the quality gap.

Proposition 3. *With endogenous quality and second-degree price discrimination,*

- (i) *price is salient as $a \rightarrow \infty$ and b is fixed,*
- (ii) *quality is salient as $b \rightarrow 0$ and a is fixed.*

1.6 Profit from Salient Consumers

1.6.1 Quality vs. Price Salience – Which is more profitable?

So far I have analyzed whether price or quality becomes salient through standard price-discrimination. But which is more profitable – quality- or price-salience? First, consider first-degree price discrimination. From (1.14) in Section 1.5.1, we can express the difference in price of the high-quality good under quality- and price-salience as

$$\frac{1}{\delta} \theta_H \left(\frac{b}{ac} \frac{1}{\delta} \theta_H \right)^{\frac{b}{a-b}} - \delta \theta_H \left(\frac{b}{ac} \delta \theta_H \right)^{\frac{b}{a-b}} = \theta_H^{\frac{a}{a-b}} \left(\frac{b}{ac} \right)^{\frac{b}{a-b}} \left(\frac{1}{\delta}^{\frac{a}{a-b}} - \delta^{\frac{a}{a-b}} \right) > 0$$

The cost difference is

$$c \left(\frac{b}{ac} \frac{1}{\delta} \theta_H \right)^{\frac{a}{a-b}} - c \left(\frac{b}{ac} \delta \theta_H \right)^{\frac{a}{a-b}} = c \theta_H^{\frac{a}{a-b}} \left(\frac{b}{ac} \right)^{\frac{a}{a-b}} \left(\frac{1}{\delta}^{\frac{a}{a-b}} - \delta^{\frac{a}{a-b}} \right) > 0$$

While the monopolist can charge a higher price under quality-salience, it provides a higher quality and hence incurs a higher cost also. For the high-quality good, profit from quality-salience will be larger than profit from price-salience if the price-difference is larger than the cost-difference:

$$\theta_H^{\frac{a}{a-b}} \left(\frac{b}{ac} \right)^{\frac{b}{a-b}} \left(\frac{1}{\delta}^{\frac{a}{a-b}} - \delta^{\frac{a}{a-b}} \right) > c \theta_H^{\frac{a}{a-b}} \left(\frac{b}{ac} \right)^{\frac{a}{a-b}} \left(\frac{1}{\delta}^{\frac{a}{a-b}} - \delta^{\frac{a}{a-b}} \right) \iff a > b \quad (1.21)$$

which is satisfied under Assumption 2. By similar logic, profit from selling the low-quality good under quality-salience is more profitable than under price-salience. This result should not be surprising since quality-salience makes customers willing to pay more for the *same* quality, whereas price-salience makes them willing to pay less for the *same* quality. As a result, the monopolist can charge a higher price without having to incur the cost to upgrade quality when quality is salient, and profits are higher.

Next, consider second-degree price discrimination. From (1.19) in Section 1.5.2, the price difference for the high-quality good between the two regimes is

$$\left(\theta_H^{\frac{a}{a-b}} \left(\frac{b}{ac} \right)^{\frac{b}{a-b}} - (\theta_H - \theta_L) \left[\frac{b}{ac} \Theta \right]^{\frac{b}{a-b}} \right) \left(\frac{1}{\delta}^{\frac{a}{a-b}} - \delta^{\frac{a}{a-b}} \right)$$

and the cost difference is

$$c \left(\frac{b}{ac} \frac{1}{\delta} \theta_H \right)^{\frac{a}{a-b}} - c \left(\frac{b}{ac} \delta \theta_H \right)^{\frac{a}{a-b}} = c \theta_H^{\frac{a}{a-b}} \left(\frac{b}{ac} \right)^{\frac{a}{a-b}} \left(\frac{1}{\delta}^{\frac{a}{a-b}} - \delta^{\frac{a}{a-b}} \right)$$

The price difference is larger if

$$\begin{aligned} \left(\theta_H^{\frac{a}{a-b}} \left(\frac{b}{ac} \right)^{\frac{b}{a-b}} - (\theta_H - \theta_L) \left[\frac{b}{ac} \Theta \right]^{\frac{b}{a-b}} \right) \left(\frac{1}{\delta}^{\frac{a}{a-b}} - \delta^{\frac{a}{a-b}} \right) &> c \theta_H^{\frac{a}{a-b}} \left(\frac{b}{ac} \right)^{\frac{a}{a-b}} \left(\frac{1}{\delta}^{\frac{a}{a-b}} - \delta^{\frac{a}{a-b}} \right) \\ a &> \frac{\theta_H^{\frac{a}{a-b}}}{\theta_H^{\frac{a}{a-b}} - (\theta_H - \theta_L) \Theta^{\frac{b}{a-b}}} b \end{aligned} \quad (1.22)$$

which is a stricter requirement than Assumption 2. The following proposition summarizes:

Proposition 4. *Quality-salience is always more profitable than price-salience under first-degree price-discrimination but only sometimes more profitable under second-degree price discrimination.*

1.6.2 Inducing Quality-Salience

It can be shown that with linear costs, the monopolist can induce quality-salience when price is salient by default. In the previous section, I show that under first-degree price discrimination, profit from quality-salience is always higher than from price-salience or no-salience. I now show that the monopolist, by giving a sufficiently small discount to the high-type, can induce quality-salience when costs rise linearly

with the upgrade of quality. Instead of charging p_H , the monopolist will charge $p'_H = p_H - \epsilon$ to the high-type. The modified high-type participation constraint does *not* bind: $p'_H < \frac{\theta_H}{\delta} q_H^b$, i.e. the high-type gets positive surplus. Substituting $p'_H = \frac{\theta_H}{\delta} q_H^b - \epsilon$ instead of $p_H = \frac{\theta_H}{\delta} q_H^b$, we get the following profit function that the monopolist maximizes:

$$\max_{\{q_H, q_L\}} \pi^{QS} = \lambda \left(\frac{\theta_H}{\delta} q_H^b - \epsilon - c q_H \right) + (1 - \lambda) \left(\frac{\theta_L}{\delta} q_L^b - c q_L \right) \quad (1.23)$$

This gives

$$\frac{q_L}{p_L} = \left(\frac{\theta_L}{\delta} \right)^{\frac{1-b}{1-b}} \left(\frac{b}{c} \right)^{\frac{1-b}{1-b}} = \frac{b}{c} = \left(\frac{\theta_H}{\delta} \right)^{\frac{1-b}{1-b}} \left(\frac{b}{c} \right)^{\frac{1-b}{1-b}} = \frac{q_H}{p_H}$$

Given $p'_H < p_H$, it must be that $\frac{q_L}{p_L} < \frac{q_H}{p_H}$. In the appendix, I show that $\pi^{QS} = \left(\frac{1}{\delta} \right)^{\frac{1}{1-b}} \pi^{NS} - \lambda \epsilon$ where π^{NS} is profit when neither price nor quality is salient. Hence $\pi^{QS} > \pi^{NS}$ when

$$\underbrace{\left(\frac{1}{\delta} \right)^{\frac{1}{1-b}} \pi^{NS} - \lambda \epsilon}_{\text{gain from inducing quality salience}} > \underbrace{\lambda \epsilon}_{\text{total discount given to high-types}} \quad (1.24)$$

I make a few remarks here. First, with $\delta = 1$, i.e. with standard thinkers, giving a discount would never be a good idea. Second, (1.24) provides an intuitive expression that shows inducing quality-salience is profitable only when the gain from doing so exceeds the discount given to high-types to achieve such salience. Third, this inequality is harder to satisfy with a higher fraction λ of high-types or larger drops in marginal utility from quality upgrades (lower b or more concave utility function). The reason why an increase in λ makes it harder is simple – more high-types mean a larger total discount conditional on a fixed discount per high-type buyer. The reason

why a more concave utility function makes it harder is because increases in quality is over-weighted less due to greater diminishing utility from such quality increases. Lower the distortion in weighting of quality vis-a-vis price by the salient buyer, closer is the profits from quality-salience to profits from no salience. Finally, unless there is a lower bound on the discount ϵ , this inequality (1.24) can always be satisfied for a sufficiently small ϵ . The following proposition formally states the result:

Proposition 5. *With endogenous cost and first-degree price discrimination, the monopolist can induce quality salience by providing a sufficiently small discount to the high-type and increase its profits relative to the default outcome of no salience.*

1.7 Conclusion

When consumers are attracted to certain features of a product more than others and overvalue those features, I show using a standard vertical differentiation model that a price-discriminating monopolist attempts to take advantage of such “salient” thinking by the consumers. I study both first-degree and second-degree price discrimination and demonstrate three novel results.

First, the firm always prefers quality to be salient due to higher profits under first-degree price discrimination and sometimes prefers quality-salience with second-degree price discrimination. Second, whether or not it manages to induce quality-salience depends on the interaction between consumer preferences for quality and the cost of upgrading quality and the type of price discrimination it can engage in. In the case of first-degree price discrimination, price is salient if the cost of upgrading quality is convex whereas neither price nor quality is salient when cost increases linearly in quality upgrades. This is because, in the first-best case when the monopolist extracts full surplus from both types of consumers, it passes on all costs to the buyers. Convex costs mean that doubling quality leads to more than double the cost and hence price, which in turn lead to a lower quality-per-dollar for the good, making the high price

salient. But linear costs do not have that same impact. Third, I show that the monopolist can induce quality-salience with linear costs by giving a small discount for the high-quality good to make the price ratio decrease and quality becomes salient.

When the firm cannot distinguish between buyer types, the information rent accruing to the high-valuation buyer and the downward distortion in quality of the low-quality good raises the quality ratio and lowers the price ratio so that quality becomes salient by default. In other words, the information rent and quality degradation serves two purposes – discourage the high-type from buying the low-quality good as in the standard model *and* make quality salient due to buyers being salient thinkers. If however, quality-upgrade costs are sufficiently convex, price is salient.

The analysis does have limitations. Ensuring tractability meant that utility and cost functions had to take specific forms. However, the literature on price discrimination has been even more restrictive on the choice of function forms, usually limiting study to linear utilities and costs. Tirole (1988) provide intuition for this linear form. Given this context, my attempt to study concave preferences for quality is a step forward despite using specific functions to model it.

It may be argued also that quality is often not quantifiable. While tire ratings can be given in miles, is a business-class seat twice as good as an economy-class seat? However, this did not stop the literature on quality provision and price discrimination (Spence (1975), Mussa and Rosen (1978) etc.) from analyzing firm strategy and consumer welfare. In this paper’s context, while quality-price ratios play a pivotal role, it is not necessary to have exact quality numbers in the minds of buyers for them to be influenced by the salience of price or quality.

I have also made the assumption that all consumers have a uniform salience parameter δ , i.e. they overweight or underweight the salient attribute at the same intensity. Homogeneity of preferences for quality upgrades across buyer types is not always true either. Moreover, it is possible that the convexity or concavity of cost

of quality upgrades may be different across products. Allowing heterogeneity in the salience parameter and preference and technology parameters are interesting extensions to my model and worth further investigation.

Another issue to note is that in the current setup price is salient even if the price-ratio is greater than the quality-ratio by a tiny margin and a similar issue is true when quality is salient even though the quality-ratio is only slightly bigger than the price-ratio. A more realistic model will make the salience parameter δ a function of the quality- and price- ratios. If, for example, the quality-ratio is slightly larger than the price-ratio, then δ takes a small value. If on the other hand, the quality-ratio is substantially larger than the price-ratio, then δ is also larger.

1.8 Appendix

1.8.1 Salience in the two-good case

To see why $\frac{q_H}{\bar{q}} > \frac{p_H}{\bar{p}}$ implies $\frac{q_H}{q_L} > \frac{p_H}{p_L}$, note that $\bar{q} = \frac{q_H + q_L}{2}$ and $\bar{p} = \frac{p_H + p_L}{2}$ and we have:

$$\begin{aligned}
\frac{q_H}{p_H} &> \frac{\bar{q}}{\bar{p}} \\
\frac{q_H}{p_H} &> \frac{q_H + q_L}{2} \times \frac{2}{p_H + p_L} \\
\frac{q_H}{p_H} &> \frac{q_H + q_L}{p_H + p_L} \\
q_H p_H + q_H p_L &> q_H p_H + q_L p_H \\
q_H p_L &> q_L p_H \\
\frac{q_H}{q_L} &> \frac{p_H}{p_L}
\end{aligned}$$

1.8.2 Profit from quality-salience expressed in terms of profit from no salience

From (1.14) in Section 1.5.1, we have optimal qualities $q_i = \left(\frac{b}{ac}\Delta\theta_i\right)^{\frac{1}{1-b}}$ for $i = L, H$ in the case of first-degree price discrimination. Specifically, optimal quality when quality is salient and cost is linear is $q_i^{QS} = \left(\frac{b\theta_i}{c\delta}\right)^{\frac{1}{1-b}}$ whereas optimal quality when neither quality nor price is salient is $q_i^{NS} = \left(\frac{b\theta_i}{c}\right)^{\frac{1}{1-b}}$. So,

$$q_i^{QS} = \left(\frac{1}{\delta}\right)^{\frac{1}{1-b}} \left(\frac{b\theta_i}{c}\right)^{\frac{1}{1-b}} = \left(\frac{1}{\delta}\right)^{\frac{1}{1-b}} q_i^{NS} \quad (1.25)$$

From (1.23) in Section 1.5.1, we have the following maximization problem with quality-salience:

$$\max_{\{q_H, q_L\}} \pi^{QS} = \lambda \left(\frac{\theta_H}{\delta} (q_H^{QS})^b - \epsilon - c q_H^{QS} \right) + (1 - \lambda) \left(\frac{\theta_L}{\delta} (q_L^{QS})^b - c q_L^{QS} \right)$$

Plugging in the optimal qualities from (1.25) above, we get maximized profit from quality-salience:

$$\begin{aligned} \pi^{QS} &= \lambda \left[\frac{\theta_H}{\delta} \left(\frac{1}{\delta}\right)^{\frac{b}{1-b}} (q_H^{NS})^b - \epsilon - c \left(\frac{1}{\delta}\right)^{\frac{1}{1-b}} q_H^{NS} \right] + \\ &\quad (1 - \lambda) \left[\frac{\theta_L}{\delta} \left(\frac{1}{\delta}\right)^{\frac{b}{1-b}} (q_L^{NS})^b - \epsilon - c \left(\frac{1}{\delta}\right)^{\frac{1}{1-b}} q_L^{NS} \right] \\ &= \left(\frac{1}{\delta}\right)^{\frac{1}{1-b}} \pi^{NS} - \lambda \epsilon \end{aligned}$$

1.8.3 Second-Order Conditions

Endogenous Quality: First-Degree Price Discrimination

The first derivatives are:

$$\frac{\partial \pi^{FD}}{\partial q_H} = b\lambda\theta_H q_H^{b-1} - \lambda ac q_H^{a-1} \quad \text{and} \quad \frac{\partial \pi^{FD}}{\partial q_L} = b(1 - \lambda)\theta_L q_L^{b-1} - \lambda ac q_L^{a-1}$$

The second derivatives are:

$$\frac{\partial^2 \pi^{FD}}{\partial q_H^2} = (b-1)b\lambda\theta_H q_H^{b-2} - \lambda(a-1)acq_H^{a-2}$$

and

$$\frac{\partial^2 \pi^{FD}}{\partial q_L^2} = (b-1)b(1-\lambda)\theta_L q_L^{b-2} - (1-\lambda)(a-1)acq_L^{a-2}$$

$$\frac{\partial^2 \pi^{FD}}{\partial q_H^2} < 0 \text{ if}$$

$$(b-1)b\lambda\theta_H q_H^{b-2} < \lambda(a-1)acq_H^{a-2} \iff a > b$$

The exact same condition arises from requiring $\frac{\partial^2 \pi^{FD}}{\partial q_L^2} < 0$.

The cross-partial derivatives $\frac{\partial^2 \pi^{FD}}{\partial q_H \partial q_L}$ and $\frac{\partial^2 \pi^{FD}}{\partial q_L \partial q_H}$ are both 0. The condition $a > b$ leads to $\frac{\partial^2 \pi^{FD}}{\partial q_H^2} \times \frac{\partial^2 \pi^{FD}}{\partial q_L^2} > 0$ and hence the Hessian is negative definite and (q_H^{FD}, q_L^{FD}) are maxima.

Endogenous Quality: Second-Degree Price Discrimination

The first derivatives are:

$$\frac{\partial \pi^{SD}}{\partial q_H} = b\lambda\theta_H q_H^{b-1} - \lambda acq_H^{a-1} \quad \text{and} \quad \frac{\partial \pi^{SD}}{\partial q_L} = b(1-\lambda)\theta_L q_L^{b-1} - (1-\lambda)acq_L^{a-1} - b\lambda(\theta_H - \theta_L)q_L^{b-1}$$

The second derivatives are:

$$\frac{\partial^2 \pi^{SD}}{\partial q_H^2} = (b-1)b\lambda\theta_H q_H^{b-2} - \lambda(a-1)acq_H^{a-2}$$

and

$$\frac{\partial^2 \pi^{SD}}{\partial q_L^2} = (b-1)b(1-\lambda)\theta_L q_L^{b-2} - (1-\lambda)(a-1)acq_L^{a-2} - (b-1)b\lambda(\theta_H - \theta_L)q_L^{b-2}$$

$$\frac{\partial^2 \pi^{SD}}{\partial q_H^2} < 0 \text{ if}$$

$$(b-1)b\lambda\theta_H q_H^{b-2} < \lambda(a-1)acq_H^{a-2} \iff a > b$$

which is the same condition as under first-degree price discrimination since the derivative has not changed. However, now the second derivative in regards to the low-quality good *has* changed and hence $\frac{\partial^2 \pi^{SD}}{\partial q_L^2} < 0$ if

$$[(b-1)b(1-\lambda)\theta_L - (b-1)b\lambda\theta_H - \theta_L]q_L^{b-2} < (1-\lambda)(a-1)acq_L^{a-2} \iff a > b\hat{\Theta}$$

where $\hat{\Theta} = \frac{\theta_L - \lambda\theta_H}{\theta_L - \frac{\lambda}{1-\lambda}(\theta_H - \theta_L)}$. $\hat{\Theta}$ is less than 1 if $\lambda\theta_H < \theta_L$, which is true under Assumption 3. Since $\hat{\Theta} < 1$, the condition $a > b\hat{\Theta}$ is weaker than the condition $a > b$ and is thus satisfied if $a > b$.

The cross-partial derivatives $\frac{\partial^2 \pi^{FD}}{\partial q_H \partial q_L}$ and $\frac{\partial^2 \pi^{FD}}{\partial q_L \partial q_H}$ are again both 0. The condition $a > b$ leads to $\frac{\partial^2 \pi^{FD}}{\partial q_H^2} \times \frac{\partial^2 \pi^{FD}}{\partial q_L^2} > 0$ and hence the Hessian is negative definite and (q_H^{SD}, q_L^{SD}) are maxima.

1.8.4 Condition for Separating Equilibrium

Salience will only arise if the firm sells two goods instead of one. To ensure a separating equilibrium, i.e. the firm sells two different goods to two customers instead of a pooling equilibrium whereby it sells to both customers either the low-quality or high-quality but does not offer both goods at the same time, the condition is that going from low to high quality increases surplus proportionally more for high-type customers than for the low-types (Anderson and Dana Jr, 2009):¹⁶

$$\frac{\theta_H q_H^b - q_H^a}{\theta_H q_H^b - q_H^a} > \frac{\theta_H q_H^b - q_H^a}{\theta_H q_H^b - q_H^a}$$

This too is satisfied if $a > b$, i.e. Assumption 2.

¹⁶See pg. 225 of (Belleflamme and Peitz, 2015) for the exact condition that I use here.

CHAPTER 2

THE IMPACT OF UBER AND LYFT ON TAXI SERVICE QUALITY: EVIDENCE FROM NEW YORK CITY

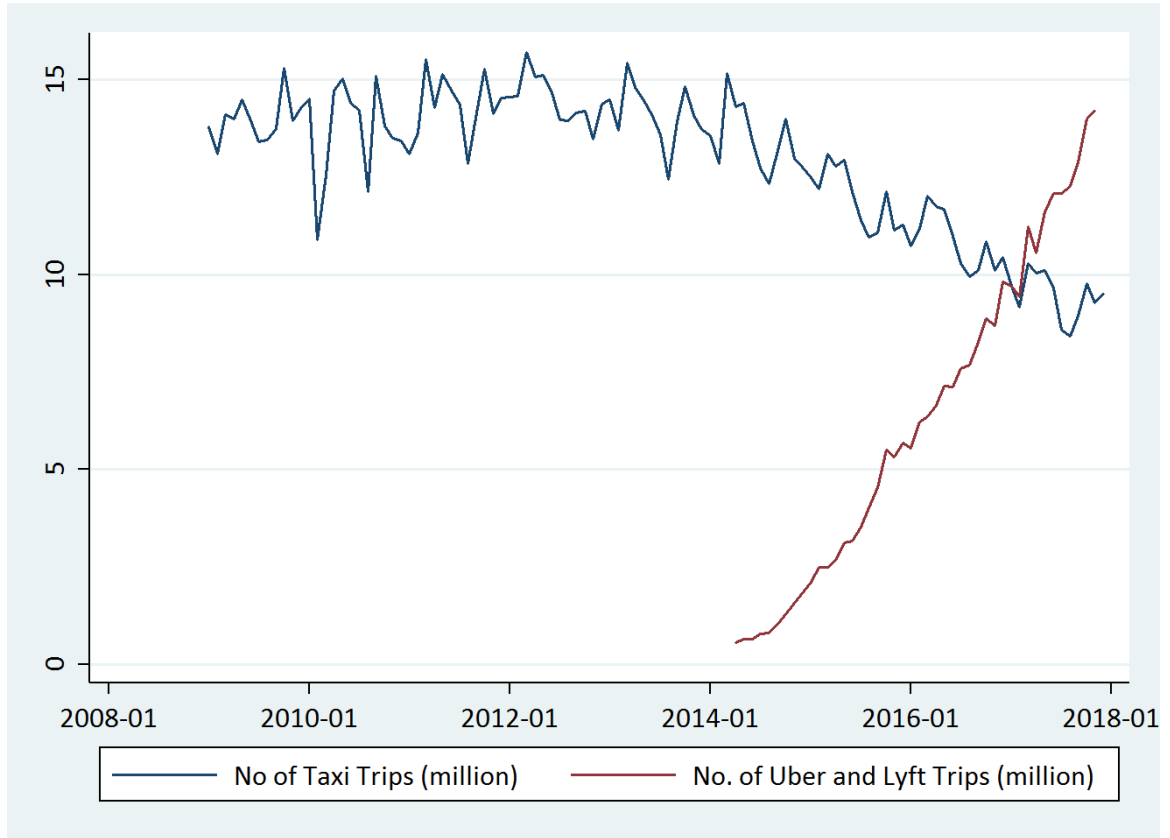
The arrival of ride-sharing services¹ such as Uber and Lyft has extensively changed many aspects of our lives. In less than four years after entry, the total number of Uber and Lyft trips surpassed the number of taxi trips in New York City (Figure 2.1). Their importance is reflected by the growing body of literature studying the effects of ride-sharing on labor supply patterns, public transit usage, congestion, road fatalities and more.

In this paper, we focus on how the entry of such ride-sharing services has affected service quality provided by taxi drivers in New York City. We do this by looking at changes in the number of complaints made against these taxi drivers. Taxi riders or pedestrians can make calls to 311, a service offered by most U.S. cities that is similar to 911 but for non-emergency purposes, to complain against taxi drivers. Complaints can relate to rude behavior, unsafe driving, fare refusal, unclean vehicles and several other quality dimensions. Given the importance of taxis in the economy and even greater importance of studying the effects of the sharing economy, we ask if competition from ride-sharing services has led to taxi drivers improving or worsening their service quality.

Economic theory predicts, all else constant, that incumbent firms will increase quality as they face more competition to maintain market share and profits. Several papers provide empirical evidence in favor of the positive impact of competition

¹A more formal and comprehensive term is Transportation Network Companies (TNC). Since ride-sharing has been commonly used as an equivalent term for TNCs in the media and past literature, we stick to that convention. Also note that ride-sharing is a misnomer since the vast majority of Uber and Lyft drivers are commercial drivers and not regular people “sharing” their cars.

Figure 2.1: Number of taxi and Uber/Lyft pickups



Taxi, Uber and Lyft trip data was aggregated to generate monthly data for this figure. Uber trip data is missing from its launch in NYC in July 2012 till the end of March 2014. Uber and Lyft data is also missing for the months October to December 2014.

on service quality in other industries: greater competition induces Internet Service Providers (ISP) to offer higher speeds (Wilson, 2015); mergers between airlines tend to reduce flight frequencies and increase flight delays (Mazzeo, 2003); and banks provide higher branch density and more employees per branch in larger markets where they face more competition (Dick, 2007). Therefore, theory and empirical evidence appear to lead us to expect that competition improves quality of service.

However, there are several issues to be aware of when we apply this general idea to the taxi industry. First, taxi drivers normally do not have repeat passengers which means that drivers do not have the incentive to build a reputation. Second, reputation building may not work even at the firm-level. This is because the taxi industry is characterized by a very low level of market share concentration, with

the industry’s four largest players in New York accounting for less than 5.0% of total industry revenue in 2017 (IBISWorld, 2018). Third, it is questionable to what extent passengers pay attention to and remember the name of the taxi company they used unlike in the case of the name of the restaurant they last ate at. The lack of importance of taxi brand names diminishes the incentives of taxi companies to invest in better service quality also. Thus it is not a priori clear whether increasing competition from ride-sharing services will have a positive or negative impact on taxi service quality.

We use novel incident-level complaints data that, to our knowledge, has not been analyzed by anyone before. Combining this dataset with the widely used NYC taxi trips data and Uber and Lyft trips data, we find that the growth in ride-sharing services coincides with an increase in complaints against taxi drivers. We focus on complaints that mostly frequently recur during the sample period.

We find evidence that taxi drivers have been driving more aggressively after the arrival of Uber and Lyft. Complaints regarding unsafe driving have a statistically significant positive relationship with growth in Uber and Lyft. We obtain similar results for complaints related to route, discourteous behavior and tips given to taxi drivers, such as failure to issue a receipt for the tip.

We also find that competition from Uber and Lyft has led at first to a rise and then a fall in refusals by taxi drivers to take the ride to his/her destination. Pickup refusals in theory may increase or decrease due to more competition. On the one hand, more competition can increase the opportunity cost of time. For instance, accepting a short-distance low-paying fare prevents the driver from potentially finding a long-distance higher-paying fare had he waited a bit longer.² On the other hand, more competition leads to decreased market share which can increase the desperation of

²Anecdotal evidence reveals taxi drivers’ reluctance to accept short fares. This may be due to the fare structure, search costs and wait times in between trips or a combination of the preceding factors.

taxi drivers and make them less picky about which fares to accept or refuse.

We consider a variety of alternative explanations for the rise in complaints. Increasing use of smartphones which may make it easier to complain, rising expectations by riders who now have access to better cars through Uber and Lyft, decrease in enforcement of penalties against taxi drivers for violations and a host of other factors may have contributed to the phenomena we document. Our results are robust to controlling for these confounding factors.

More importantly, there may be reverse causality between complaints and Uber and Lyft penetration. Dissatisfied passengers complain more but some of them also stop using the service they are dissatisfied with and switch to a competitor. So higher complaints may imply more riders are switching to ride-sharing services, leading to both higher Uber and Lyft trips and lower taxi trips. We use instrument variables to mitigate this concern. In particular, we use Bartik shift-shares (Bartik, 1991) that has been used in empirical contexts similar to ours. Our IV estimation results deliver a similar story to what we find using OLS – more competition leads to more complaints.

Beyond showing this primary result, we investigate this relationship between penetration of Uber and Lyft and taxi service quality for each of the five boroughs in New York. Further, we look at this relationship year by year. Our results confirm expectations. Increase in most types of complaints is significant in the busiest borough of Manhattan and are also significant in the early years after the entry of Uber (e.g. 2014 and 2015) whereas the relationship fades in later years (e.g. 2016 and 2017) likely to the industry transitioning to a new equilibrium.

We also provide a likely cause for the uptick in complaints. Using driver-level data, we show that high-income drivers also tend to be the ones with more complaints against them. With Uber and Lyft capturing market share and reducing incomes, we then show that low-income drivers stopped driving taxis more than high-income

drivers. In other words, the high-income taxi drivers were better able to withstand competition. But the unintended effect was that these high-income high-complaint taxi drivers remaining with taxis and the low-income low-complaint drivers leaving changed the decomposition of “good” vs. “bad” drivers, leading to an overall decline in service quality, despite individual drivers not necessarily changing their behavior.

Our paper has important policy implications. For example, consider taxi riders’ complaints about pick-up refusals. A taxi driver may intentionally refuse to pick up a passenger when he/she finds out that the rider’s destination is not attractive.³ Some of those denied passengers may switch to alternative transport such as Uber/Lyft or the public transit system. However, other taxi users may not be able to find such an alternative.⁴ This would imply that their welfare has declined due to competition from ride-sharing services. In addition, our empirical results support the hypothesis that incumbent service quality may not always increase in response to new entrants in a market where there is a relatively low market concentration and service providers do not have repeat customers.

2.1 Related Literature

Our paper is closely related to Wallsten (2015) who study the impact of Uber on taxi complaints in New York City and Chicago. He finds that total complaints in NYC had been declining before Uber entered, but has declined faster since then. He also reports that complaints of several types have declined since Uber started operating in Chicago. There are several critical differences in methodology between our study and his. We use incident-level complaint data *by type* in NYC, whereas he uses aggregate monthly data. The higher resolution data allows us to analyze driver behavior at the taxi-zone-level rather than at the city level. There is considerable heterogeneity

³This may be either because the destination is nearby (short rides are usually less profitable per mile) or because it is in a high-crime area or something else.

⁴For example, less digitally-savvy people, perhaps from an older generation, may not be familiar with using smart-phones to hail Uber.

among the different parts of New York City in regards to taxi usage and also the extent to which Uber and Lyft has penetrated. We exploit this heterogeneity and also benefit from a panel data setting, while Wallsten, 2015 was limited to using variation over time alone given that his cross-section was the whole city and hence one unit. Another advantage in our approach is how we measure the penetration of ride-sharing services into the market. Wallsten (2015) used a Google Trends variable for the search term ‘Uber’ to proxy for competition from ride-sharing service; we use Uber/Lyft trip-level data which is far more accurate in capturing the extent of market penetration by these ride-sharing services.

Another study on Uber’s impact on taxi service quality is by Puranam (2017) who reports that consumer opinion on traditional taxi services, measured by favorable discussion in a leading online reviews portal for taxi services, improved after Uber’s entry in San Francisco in regards to pricing and wait times. We believe the measure we use to gauge changes in service quality, i.e. actual complaints made to taxi or city authorities, is better than opinions expressed on a website. This is especially true for complaints by non-passengers since a quick phone call is more likely than a website visit.

In addition to the literature on the impact of ridesharing on taxi service quality, our paper also contributes to the growing body of literature on the many effects of the arrival of Uber and Lyft beyond that of taxi service quality. Shapiro (2018) finds that Uber’s technology of matching drivers with riders provides the most benefit in the least dense areas, i.e. those under-served by taxis, since Uber shortens the wait time more in less dense areas. Hall *et al.* (2017) analyze the impact of Uber’s “surge pricing” by utilizing a quasi-natural experiment where the Uber app temporarily stopped working due to a technical glitch on New Year’s Eve. They show that surge pricing can dramatically increase driver labor supply, thus resulting in an increased number of driver-rider matches and less variation in wait times before a match. Similarly,

Chen and Sheldon (2015) find that drivers work longer sessions and provided more rides in response to unexpected changes in earnings from surge pricing.

The other aspect of Uber that has affected driver supply decisions is its flexible hours. Hall and Krueger (2018) contrast demographics of Uber drivers with that of taxi drivers and find considerably more heterogeneity among the former. In particular, more women and younger drivers are prevalent on Uber. They posit that this is likely due to such people having other jobs or studies and only manage to work irregular hours on the platform, which is usually not possible with taxis.⁵

Our paper shares some similarity with Cook *et al.* (2018) in finding a link between driver’s income and driving behavior. They show that the gender gap in earnings among Uber drivers is related to the extent to which they speed, their choice of passengers, and their choice of location to pick up passengers. Their research implies that if a taxicab driver’s income has declined due to competition from ride-sharing service providers, their driving behavior could be affected just like those of Uber drivers. While we cannot verify the exact linkage between a taxi driver’s income and the driver’s driving behavior due to data limitations, it is not a stretch to conjecture that intense competition from Uber and Lyft might have affected taxi drivers’ income on average and thus some drivers have started to drive more aggressively to make up for the loss in income.

There are effects on the demand side as well. Greenwood and Wattal (2015) find that the introduction of Uber contributed to a significant drop in fatalities in California, particularly in large cities. The effect goes away during periods of surge pricing indicating that DUI violators were likely engaging in such practices due to relatively higher taxi fares prior to the arrival of Uber and Lyft.

⁵Usually, taxi companies lease out taxis to drivers for 12-hour shifts for a fixed fee. Drivers then decide the number of hours (up to a maximum of 12) they would like to drive. Fewer hours driven result in lower income but with the same fixed leasing fee. Drivers therefore tend to drive a full shift, effectively ruling out the possibility of a part-time career or a second job. On the other hand, there are no leasing fees drivers pay directly to Uber or Lyft. Instead, payment to these platforms are on a per-trip basis, encouraging people to drive as much or as little as they want.

Another important issue motivated by the advent of ride-sharing service is its impact on public transit usage. Hall *et al.* (2017) find that entry by Uber resulted in an increase in public transit use in large cities, but decreased in smaller cities. Multiple other studies and surveys show that ridership in general has decreased due to ride-sharing services. Babar and Burtch (2017) look further into the different types of public transit and find that subway and commuter rail travel increased post-entry of Uber and Lyft, but city bus travel decreased.

The usual pattern of entry in most U.S. cities has been Uber first, followed by Lyft a few months later. Sadowsky and Nelson (2017) find that while the entry by Uber may have had solved the last-mile problem and induced increased usage of public transport, the entry of Lyft caused price competition between the two ride-sharing companies. The resulting increase in affordability of ride-sharing decreased public transport use.⁶

Li *et al.* (2016) find that the arrival of Uber caused congestion to decrease in urban areas across the U.S. They argue that this maybe due to increased vehicle occupancy and reduced car ownership and even increased substitution of public transit and other modes of transport instead of cars.⁷

2.2 Data

2.2.1 Taxi trips

We obtained trip-level NYC yellow taxi data for the time period from January 2009 to December 2017 from the New York City Taxi and Limousine Commission (TLC).⁸

⁶Bliss, L. (2017, October 12) The Ride-Hailing Effect: More Cars, More Trips, More Miles. *CityLab*. Retrieved from <https://www.citylab.com/transportation/2017/10/the-ride-hailing-effect-more-cars-more-trips-more-miles/542592/>

⁷Also see LeBlack, S. (2018, February 25) Studies are increasingly clear: Uber and Lyft congest cities. *Chicago Tribune*. Retrieved from <http://www.chicagotribune.com/bluesky/technology/ct-uber-lyft-congestion-20180225-story.html>

⁸It is publicly available at the TLC website <https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page>. The TLC continues to update this dataset to include taxi trips from the latest months and currently has data till June

Table 2.1: Description of datasets

	Source	Period Start	Period End	Resolution	Location	Observations
Taxi trips	TLC	Jan 2009	Dec 2017	Trip Level	Lat/Long [†]	1.6 billion
Uber & Lyft trips	TLC	Jan 2015	Dec 2017	Trip Level	taxi-zone	88 million
Uber & Lyft trips	TLC	April 2014	Sep 2014	Trip Level	Lat/Long	4.5 million
Complaints	DoITT	Jan 2010	Dec 2017	Incident Level	Lat/Long	519,892

The New York Taxi and Limousine Commission (TLC) uploads all past taxi and FHV trip data to <https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page>. Taxi trip data obtained by FiveThirtyEight using a FOIL request to TLC is at <https://github.com/fivethirtyeight/uber-tlc-foil-response>. Complaints data without complaint type categorization is publicly available at <https://data.cityofnewyork.us/Social-Services/311-Taxi-Complaints/uppf-z66u>. We obtained complaints data categorized by type through a FOIL request from the Department of Information Technology and Telecommunications (DoITT). [†]TLC stopped providing latitude and longitude for taxi trips starting July 1, 2016. Data from that date onwards include taxi-zone only.

This data has been used in the past by several other papers studying taxis and Uber, some of which we have cited in the literature review section.

Each trip-level observation contains pick-up and drop-off date and time, geographic location in latitude and longitude of the pick-up and drop-off points, trip distance, fare, etc. Perhaps due to privacy reasons, the TLC stopped providing latitude and longitude information beginning July 2016. Data since then includes the pickup and dropoff “taxi-zones” only. Taxi-zones are areas defined by the TLC for administrative purposes. They are similar to zip codes (Figure 2.2). There are 263 zones across the five boroughs of Manhattan, Queens, Brooklyn, Bronx, and Staten Island. All our analyses use trip-level and complaints-level data aggregated to the zone-week level, i.e. the total number of taxi or Uber/Lyft trips and complaints in a given week in a given taxi-zone. We elaborate on this in Section 2.4.

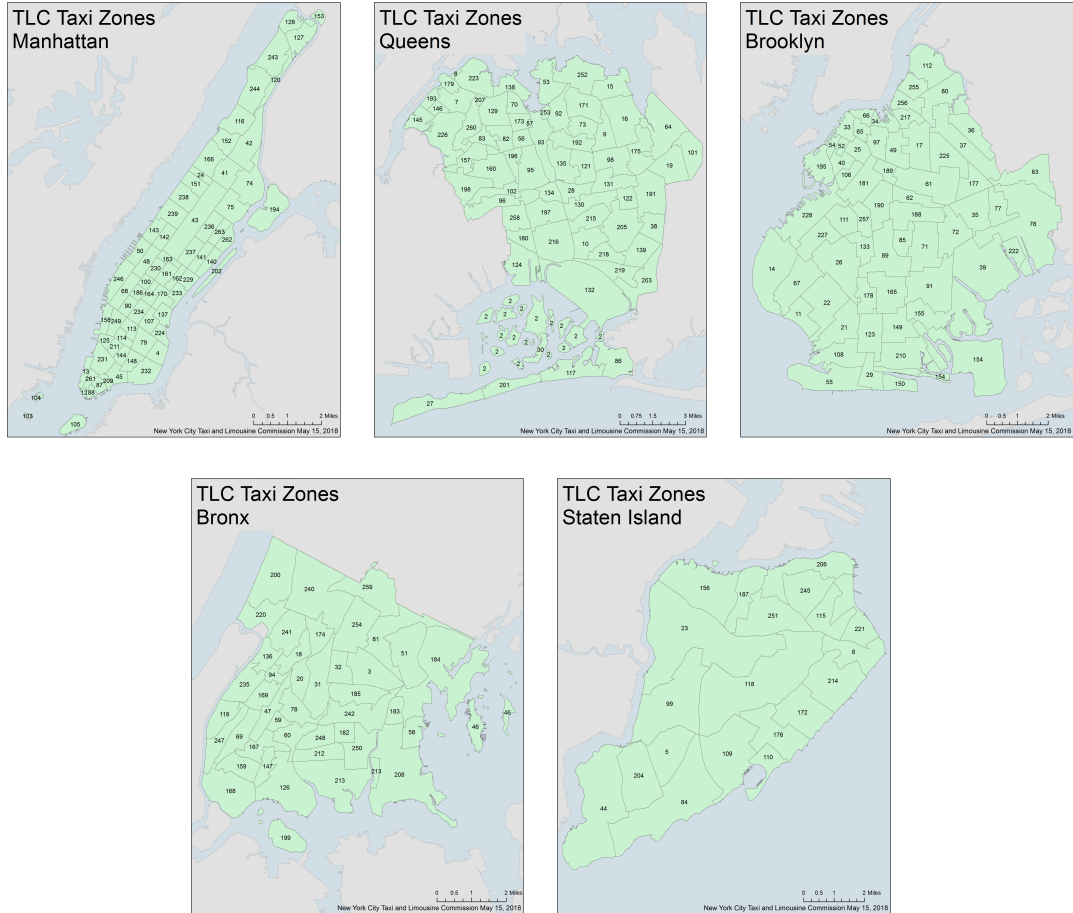
2.2.2 Uber and Lyft trips

Trip-level Uber and Lyft data comes from two different sources. The first comes from the TLC directly. The TLC classifies Uber and Lyft to be “For-Hire Vehicles” and released trip data of FHV companies for the period starting January 2015 and continues to update this dataset to include recent months.⁹

2018.

⁹Available publicly at the same link cited in the previous footnote. The latest month for which data is available for taxi and FHV companies as of this writing is June 2018.

Figure 2.2: taxi-zones by borough



Maps downloaded from TLC website at <https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page>.

We obtained Uber and Lyft trip data for part of the year 2014 from a different source. Prior to making FHV trip available on its website, the TLC had provided FHV trip data to FiveThirtyEight for the period May 2014 to June 2015 (with the exception of the last three months in 2014) in lieu of a Freedom of Information Law request.¹⁰

Uber entered New York in May 2011 with their premium service “UberBlack” which has remained small and serves a niche market, in competition with limousine services. “UberX”, their economy line which competes directly with taxis, was

¹⁰Available at <https://github.com/fivethirtyeight/uber-tlc-foil-response>

Table 2.2: Summary Statistics: All variables except complaints (Weekly, zone-level)

	Observations	Mean	St. Dev.	Min	Max
Average Taxi Trip Duration (minutes)	119,589	15.90	9.92	0.05	299.65
Average Taxi Trip Speed (mph)	119,589	16.17	4.57	0.03	79.80
Average Taxi Trip Distance (miles)	52,836	4.50	4.35	0.00	99.22
Average Tip per Trip (\$)	52,836	2.24	3.88	0.00	269.74
No. of Boro Pickups (000s)	119,589	0.49	1.87	0.00	21.70
No. of Rodent Sightings	73,886	3.22	3.24	1.00	310.00
No of Taxi Pickups (000s)	119,589	11.60	25.91	0.00	172.69
No. of Uber and Lyft Pickups (000s)	45,451	6.09	9.03	0.00	68.86

The unit of observation is taxi-zone-week. Complaints data cover the period starting January 2010 and ending December 2017. Taxi trip data start at January 2009 and end at December 2017. Uber and Lyft trip data cover the 6 months in 2014 from April to September and all of 2015, 2016 and 2017. Average trip duration is computed using pickup and dropoff times available in the taxi trips data.

launched in July 2012. Lyft entered later in August 2014. In May 2014, the first month for which we have data for Uber, it had roughly half a million trips on its platform. In contrast, in November 2017, the last month for which we have data for all days,¹¹ there were more than 14 million trips (Figure 2.1). We thus believe the early period for which data is missing, the period from July 2012 to April 2014, is a relatively less crucial period and the lack of this period’s data likely does not significantly affect our ability to determine the impact of ride-sharing services on taxi service quality. Furthermore, in the early days after Uber’s launch, it was not as well-known and the taxi drivers might not have felt a substantial threat from Uber at that early stage. As a result, any behavioral response from taxi drivers was likely not large.

2.2.3 Complaints against taxi drivers

Similar to 9-1-1, some cities in the U.S. have a 3-1-1 service residents can use to report a variety of issues such as dirty sidewalks, damaged trees etc. Taxi riders also use this number to report any issues they face when dealing with taxi drivers. The Department of Information Technology & Telecommunications (DoITT) of NYC makes data on all such reports through 3-1-1 publicly available on the NYC OpenData

¹¹We have Uber and Lyft data for the first one week of December 2017 only.

Table 2.3: Summary Statistics: All complaints (Weekly, zone-level)

	Mean	St. Dev.	Min	Max
AC, Heat, Radio Refused	0.00 [†]	0.01	0	1
Broken or Missing Equipment	0.03	0.19	0	4
Cellphone Use	0.05	0.25	0	13
Combined Pickups	0.00	0.02	0	1
Denied Request	0.08	0.33	0	17
Discourteous	0.20	0.58	0	35
Dropoff Refused	0.00	0.05	0	2
Fare Tip	0.29	0.74	0	14
Insurance Request	0.00	0.04	0	2
Insurance Request, Non-Passengers	0.03	0.17	0	4
Insurance Request, Passengers	0.01	0.11	0	3
License Not Displayed	0.02	0.15	0	6
Lost Item	2.25	4.49	0	55
Pickup Refused	0.31	0.79	0	26
Route	0.11	0.37	0	6
Delay or No Show	0.00	0.03	0	2
Unauth. Pickup Location	0.02	0.42	0	62
Unauth. Vehicle Operation	0.00	0.00	0	1
Unclean or Odor	0.01	0.09	0	3
Unsafe Driving, Non-Passengers	0.32	1.32	0	105
Unsafe Driving, Passengers	0.10	0.36	0	5

[†]All mean values 0.00 are truncated to maintain consistent format. The unit of observation is taxi-zone-week. Complaints data cover the period starting January 2010 and ending December 2017. Complaints in alphabetical order. N = 106,082 for each complaint type.

website.¹². It provides data on each individual complaint made by passengers and non-passengers against taxi drivers and/or taxi companies, such as incident data, latitude and longitude of incident etc. However, this publicly available data on complaints do not contain information about the complaint *type*, i.e. whether the complaint was about rude behavior by the driver or a fare overcharge and so on.

We obtained this same dataset of complaints, but along with categorization of these complaints by type, through a FOIL request to DoITT. Specifically, this dataset two descriptors on each incident indicating the type of complaint (e.g. whether it was regarding unsafe driving or the route taken by the driver). The TLC categorizes the incidents into 21 types. We have retained the names of the original incident types as used by TLC. The dataset contains complaints for the period from January 2010 to December 2017.

The complaints dataset contain a total of 561,236 reports. Of these, 528,701

¹²<https://data.cityofnewyork.us/Social-Services/311-Taxi-Complaints/uppf-z66u> We perform a falsification test using rodent sightings reported through 3-1-1 and that data comes from the NYC OpenData site also.

Table 2.4: Summary Statistics: Main Variables (Weekly, city-level)

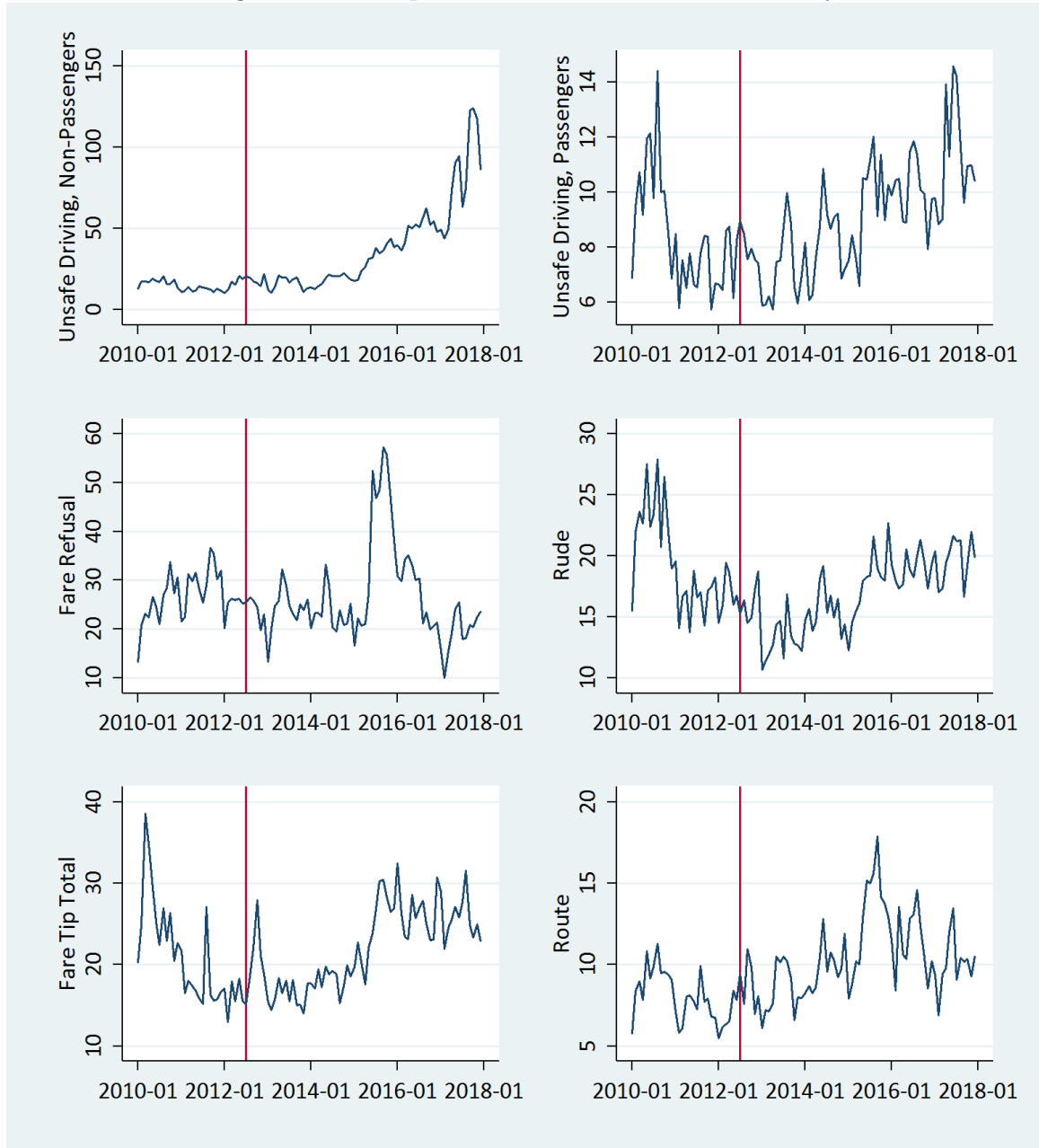
	count	mean	sd	min	max
Unsafe Driving, Non-Passengers	424	64.78	57.36	0.00	328.00
Pickup Refused	424	62.63	41.88	0.00	229.00
Fare Tip	424	59.62	35.04	0.00	222.00
Discourteous	424	41.76	24.06	0.00	104.00
Route	424	22.46	13.17	0.00	58.00
Unsafe Driving, Passengers	424	20.55	12.01	0.00	52.00
No. of Taxi trips (000s)	477	2937.52	572.83	244.55	4346.46
No. of Uber and Lyft trips (000s)	185	1728.58	893.13	0.00	3630.07

The unit of observation is city-week. Complaints ordered by weekly average, largest first. Fare Tip (total) is the sum of three separate complaint types: fare tip, fare tip credit card and fare tip receipt. Complaints data cover the 424 weeks starting January 2010 and ending December 2017. Taxi trip data cover 477 weeks start at January 2009 and end at December 2017. Uber and Lyft trip data cover 26 weeks in 2014 from April to September and another 159 weeks from 2015 to 2017.

(94.2%) have a latitude and longitude of the incident location. There are about 5,000 complaints against limousine drivers which we have dropped since that is not our focus. After we filter out compliments to drivers by taxi riders, we are left with 519,892 observations. Notice in Table 2.3 the category “Lost Items”. This comprises reports regarding lost items and are obviously not complaints against drivers and hence we do not use it in our main analysis. However, lost items provide the basis for one of our falsification tests in Section ???. While the TLC classifies tip-related complaints into three different types – fare-tip, fare-tip credit card and fare-tip receipt, for the purpose of our analyses we combined these three into one category “Fare-Tip” given the similarity of these types of incidents.

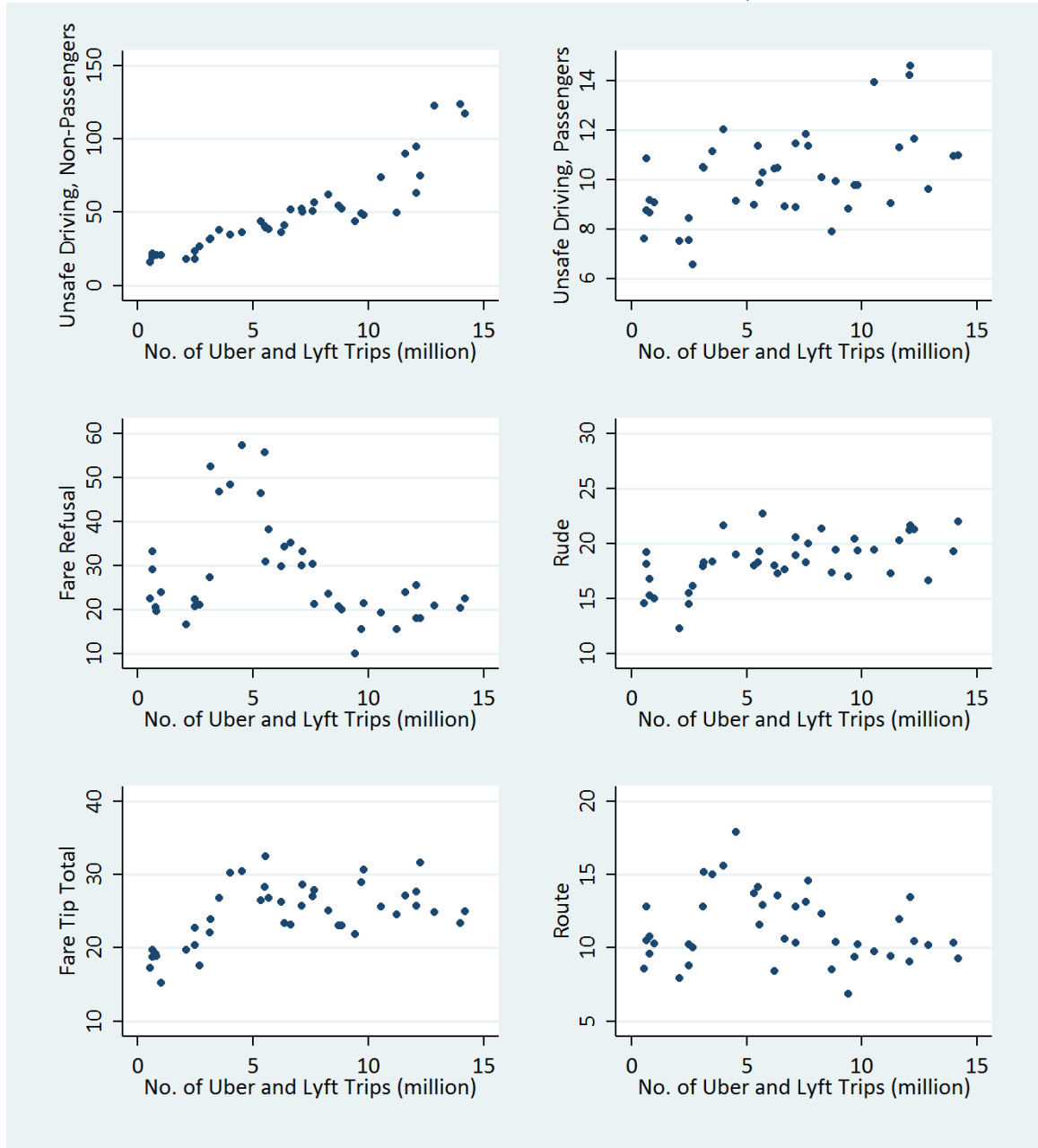
Table 2.1 provides the description of all datasets we use including source, time span, resolution, location information type and number of observations. Table 2.2 provides summary statistics for all variables except complaints at the zone-week level. Table 2.3 reports the summary statistics for all complaint types. Table 2.4 reports statistics for the main variables of interest at the city level, i.e. for the whole of New York City.

Figure 2.3: Complaints before and after Uber entry



Taxi and Uber trip data was aggregated to generate monthly data for this figure. All complaints are normalized to be per million taxi trips. Red line denote Uber entry in July 2012.

Figure 2.4: Scatterplot of complaints and Uber/Lyft trips



Taxi, Uber and Lyft trip data was aggregated to generate monthly data for this figure. All complaints are normalized to be per million taxi trips.

2.2.4 Trends in complaints

There are several interesting patterns in the data. First, we plot the normalized number of high-frequency complaints in New York before and after the entry of Uber in Figure 2.3. The vertical axis of each panel represents the number of complaints per million taxi trips and the vertical red line marks the entry of Uber. The complaints are aggregated at the monthly level for this figure. Monthly unsafe driving complaints by non-passengers in New York was around 20 per million taxi trips before Uber, but experienced a steady upward trend since then. Unsafe driving complaints by passengers did not grow as fast (panel (b)). Panel (c) illustrates complaints regarding pick-up refusals. While the trend is relatively flat, notice the large jump slightly after entry by Lyft in August 2014. Both complaints pertaining to discourteous behavior and tips to drivers fell before Uber entered but has crept up slightly since entry (panels (d) and (e)). Route complaints rose post-Uber entry although it has gone back down more recently. Since these charts show normalized complaints, these spikes cannot be attributed to changes in taxi trips.

Figure 2.4 shows scatter plots with the normalized frequency of different complaints on the vertical axes and the number of Uber and Lyft trips on the horizontal axes. Complaints other than those regarding refused pick-ups and route complaints are positively correlated with the number of Uber and Lyft trips. Pick-up refusal complaints went up rapidly with the initial increase in competition from Uber but then gradually fell after penetration by ride-sharing services reached a threshold. There is no clear pattern for route complaints.

2.3 Identification

2.3.1 Complaints as a measure of service quality

Using complaints to measure (the lack of) service quality is not without caveats. Complaints tell the reporters’ one-sided story. Taxi drivers cannot explain their behavior in their defense against complaints. For instance, it may be that the driver was genuinely not at fault and the passenger was either lying¹³ or had unreasonable expectations. Examples of unreasonable expectations is observed in the complaints data. Some riders complain that the driver did not have a toll tag which allows for easy access through toll highways and bridges, resulting in longer trips; however, drivers are not required to have toll tags by the taxi authority and hence such complaints are not an indication of low service quality. Similarly, despite years of experience and familiarity with the city and access to a GPS, some honest drivers do get lost and end up taking a longer route. Naturally, some riders become suspicious and feel such incidents are an attempt to overcharge them.

We also cannot rule out the possibility of fake complaints by other taxi drivers or even Uber drivers for reasons of enmity or otherwise. In addition, what occurs after the complaint is made is usually not recorded by taxi authorities except what disciplinary action was taken, if any. We dealt with some of these issues with appropriate data cleaning, such as dropping complaints whose descriptions indicate that the passenger complained about driver not having a toll-tag. Regarding issues such as lying and unreasonable expectations, this will cause problems with unbiased estimation only if the proportion of passengers who tend to lie or have unreasonable expectations change after the entry of Uber and Lyft. As for incidents such as when the passenger incorrectly perceives to be overcharged, there is no a priori reason to believe that the propensity to make such mistakes in judgment should change after

¹³Motives for lying is not important here; one reason may be that the passenger and driver had an argument and the former is trying to “get back” at the latter.

entry of ride-sharing services.

2.3.2 Alternative possibilities

There are several possible reasons why the number of Uber and Lyft trips and complaints may be correlated. First, there may be a pure competition effect. Uber and Lyft cars tend to be nicer on average and drivers on these platforms get rated by the passengers immediately after the trip. An average rating below a threshold set by these ride-sharing companies leads to driver deactivation and hence generates a strong incentive to provide good service. Once taxi riders use these alternative services, they may not go back to taxis. To prevent this, taxi drivers may be trying harder to please passengers relative to the period before Uber and Lyft entry, which may then lead to decrease in complaints. However, this is unlikely. Given the almost zero probability of a satisfied passenger using that same taxi driver in the future, any good service is likely to improve the image of taxis in the mind of the passenger in general rather than that specific taxi driver specifically. So better quality service by this specific driver may prevent this passenger from switching to Uber and contribute to increased (or at least not decreased) usage of taxis in general, but *other* taxi drivers will be the beneficiaries. Anticipating this, we do not expect taxi drivers to exert additional effort to provide higher service quality. In other words, there are positive externalities to providing quality service and hence we expect under-provision.

An important related issue is that consumer expectations may have gone up. As we just mentioned above, Uber cars and/or drivers are nicer, thus changing the benchmark taxi passengers are using to rate taxi drivers in their minds. They are more unhappy with taxi quality now that they have access to higher-quality Uber rides, *regardless* of actual changes in taxi service quality. The problem with this story is this should not affect non-passenger complaints. But non-passenger complaints did increase substantially as we saw in Figure 2.3.

The increase in market shares of Uber and Lyft may have coincided with an increase in complaints because of more lax enforcement of rules by the TLC against taxi drivers who have violated rules and/or caused riders to be dissatisfied. Unfortunately, we do not observe variations in enforcement intensity directly in the data. However, actions by the TLC to improve the market share of taxi drivers in the face of competition from Uber and Lyft, such as the introduction of an app to hail taxis, indicate that it would be unreasonable to expect the TLC to become more lenient with bad service quality by drivers instead of becoming stricter.

Complaints and ride-sharing penetration may also be correlated because of a rapid rise in smartphone adoption during our sample period. Internet connectivity in smartphones may have made it easier for an unhappy passenger or non-passenger to look up the contact information of the appropriate agency to make complaints. However, a sticker inside taxis near passenger seats with instructions to call 3-1-1 regarding complaints has been in taxis since before the arrival of smartphones, eliminating any concern that passengers had a harder time figuring out how to make a complaint prior to having smartphones. Even if this was not to be true, smartphones are still unlikely to have driven changes in complaints because in that case *all* complaints should have gone up, not just a subset. There is no a priori reason to believe that a decrease in difficulty to lodge a complaint should be biased towards certain types of complaint but not others. As we have seen in Figure 2.3, we do find that not all types of complaints have gone up. In particular, pickup refusal complaints had not experienced an upward trend until late 2014 even though smartphones had become widespread a considerable period before that.

Perhaps it is a change in taxi driver composition that caused taxi service quality to change. The “good” taxi drivers stopped driving taxis and moved somewhere else, either to drive for Uber or to some other career. On top of that, the drivers newly joining taxis are the “bad” ones. The reverse may also be true—the bad drivers left

taxis and new ones joining taxis are better than the outgoing ones.¹⁴ Why either case may occur is not important as long it was caused by the entry of Uber and Lyft. Rather what is important is understanding the implication of such a change in driver composition. In such a case, taxi service quality can go down because of changes in the fraction of good vs. bad drivers and not because the drivers who remained with taxis before and after Uber entry are providing worse service. Changes in driver composition is likely to be time-varying and perhaps also varying partly across taxi-zones. Using driver-level data, we investigate this particular possibility in Section 2.6.

Changes in passenger composition can also lead to changes in complaints without any corresponding change in actual taxi service quality. The fraction of “whiners” may have increased, leading to more complaints even if drivers are still providing the same quality of service. If such a change in passenger composition is caused by the arrival of Uber and Lyft, we need to factor it into our estimation.

The existing literature on the various effects of Uber suggests that Uber has also had impact on congestion. But congestion itself can affect the number of complaints against taxi drivers. Taxi drivers stuck in increasingly congested roads may decide to drive more aggressively, say by jumping red lights. They may refuse fares that will take them to congested parts of the city. We use average trip duration to measure and control for congestion.

The media and prior papers on Uber also extensively document the loss in market share of taxi drivers due to competition from these platforms. Everything else constant, fewer trips should generate fewer opportunities for passengers to be unhappy about something and hence should lead to fewer complaints. To prevent volume of

¹⁴There is a plausible reason for good drivers leaving taxis for Uber and Lyft instead of the bad ones. Given the more stringent rating systems on ride-sharing platforms as we have discussed earlier, the good taxi drivers have a better chance of survival on those platforms vis-a-vis the bad drivers who would prefer to keep driving taxis where they are less likely to be penalized for poor quality service. If Uber does provide better income opportunities, the first set of taxi drivers to leave would in that case be the good ones. Thanks to Dmitry Shishkin for pointing this out.

taxi rides to confound the relationship between competition from Uber and Lyft and the number of complaints, we control for the number of taxi trips.

Moreover, it is possible that the length of trips has changed post-Uber entry. For instance, since Uber drivers do not have the opportunity to reject less profitable short rides unlike taxi drivers, riders may have switched to Uber for these short rides more than they have for longer rides. On the other hand, longer trips provide more scope for interaction between driver and rider and hence can potentially generate more complaints. Thus leaving out taxi trip distance can cause omitted variables bias. We take this into account by average trip distance as a control variable.

It may be argued that an increase in complaints may be due to complaints by ride-sharing drivers who are likely to come across and observe taxicab drivers' behavior. In other words, more monitoring agents could have naturally led to more reports. However, we think that this behavior seems unlikely in reality because anyone reporting an incident must provide a detailed description of the incident which involves a substantial opportunity cost for Uber and Lyft drivers in the form of lost income.

In August 2013, the TLC started operating Boro Taxis.¹⁵ These Boro taxis can drop off passengers anywhere and can also pick up passengers anywhere in the outer boroughs (all five boroughs except Manhattan). However, they are not allowed to pick up passengers in the "yellow zone" of Manhattan which is south of East 96th and West 110th Streets. Any observed correlation between Uber/Lyft trips and complaints against yellow taxi drivers may actually be due to the introduction of these Boro taxis and not the arrival of ride-sharing services, at least in the case of complaints in the outer boroughs. We use Boro taxi trips to control for this.

An additional complication arises due to potential simultaneity between taxi complaints and ride-sharing and taxi trips. It is plausible that a rise in taxi complaints reflects dissatisfaction by taxi passengers who then increasingly switch to Uber lead-

¹⁵Sometimes referred to as "Green" taxis because of their green color, in contrast to regular yellow cabs.

ing to higher numbers of Uber and Lyft trips and a lower number of taxi trips. If this is true, changes in complaints can cause changes in number of Uber and Lyft trips and taxi trips. In Section 2.4.3, we elaborate on how we address this potential reverse causality using instrumental variables.

2.4 Estimation

2.4.1 Panel data construction

We combine the trip-level taxi data and Uber/Lyft data with the incident-level complaints data into a panel structure where taxi-zones $l = 1, 2, \dots, 263$ constitute the cross-section dimension. Since both trips and complaints are at the trip/incident level with date and time for each incident or trip available, we have the ability to use month, week, day or even hour to use as the time dimension. Since complaints are not very frequent, e.g. only 20 complaints of a specific type such as pickup refusal in the whole of New York City in an entire month, aggregating at a high-resolution such as hour or day would lead to excessive zeros, causing problems with estimation. On the other hand, aggregating at a low-resolution such as month and year would not allow for a variety of time fixed effects that we would like to use to control for time-varying factors. Hence, we chose to aggregate trips and complaints at the week level which provides a balance in resolution. We assigned the first seven days of each year to “Week 1”, the next seven to “Week 2” and so on. As a result, we have data for 53 weeks for each of 9 years, 2009 to 2017, for a total of 477 weeks. Note however that due to the fact that we have data on Uber and Lyfts for the years 2014 to 2017 only, not all of the sample will be used in our regressions.

2.4.2 Specification

We estimate a panel regression using the following specification:

$$Complaints_{it} = \beta_0 + \beta_1 UL_{it} + \beta_2 Taxi_{it} + \delta \mathbf{X}_{it} + \Sigma_{i \times q} + \varepsilon_{it} \quad (2.1)$$

The dependent variable $Complaints_{it}$ captures the total number of complaints of a specific type (e.g. route complaint) for taxi-zone i in week t . UL_{it} and $Taxi_{it}$ are the numbers of Uber and Lyft pickups and taxi pickups respectively. While we have data on both taxi pick-ups and drop-offs,¹⁶ we control for taxi pick-ups but not drop-offs to prevent multicollinearity since the two variables are highly correlated. We chose pickups instead of dropoffs because taxicab drivers are more in control of where they want to pick up passengers relative to where they drop them off. \mathbf{X}_{it} is the vector of all control variables except taxi trips. This comprises average taxi trip duration, average taxi trip distance, number of Boro taxi trips, and average tip amount per taxi trip.

We use zone-quarter fixed effects denoted by $\Sigma_{i \times q}$ which allows for shocks that vary across time and space. The zone-by-quarter fixed effect terms can be expressed as a product of two sets of dummies $\sum_{i=1}^{263} \sum_{q=1}^{14} \theta_{iq} I_i I_q$ where I_i and I_q are indicator functions taking on a value of one for zone i and quarter q , otherwise zero. The fourteen quarters are the sum of two quarters in 2014 and four each from 2015 to 2017 that we have Uber and Lyft data for. We include the fixed effects to address the concerns regarding identification due to several confounding factors such as changes in smartphone adoption rates, passenger expectations about quality, intensity of enforcement of rules and passenger composition. These factors vary across different parts of the city and also over time (e.g. years), but less likely over a shorter time horizon like quarters.

¹⁶Recall that we do not have Uber and Lyft drop-off data for most of the sample period

Recall from our discussion in the previous section that we suspect simultaneity in the determination of the relationships between *Complaints*, *UL* and *Taxi*. To address this, we use instrumental variables.

2.4.3 Bartik shift-shares as IV

Our two instruments are shift-shares (Bartik, 1991), which have been used in the empirical literature in international trade, development economics, labor economics and urban economics.¹⁷ The idea of Bartik shift-shares is to generate shares of some activity for each object of study (e.g. labor market, geographic region, industry) prior to a shock which are then multiplied by the total of that same activity after the shock to generate predicted shares.

In a typical labor market setting, the shock may be immigration of foreign labor and the objects of study are several industries exposed to that shock. The percentage of workers in each industry are the shares and are used to generate predicted industry shares by multiplying with the total industry employment post-immigration. In our case, the shock is the entry of Uber and Lyft and the objects of study are the taxi-zones. Fortunately we have taxi trip data from 2009, prior to the entry of these two platforms. We compute the Bartik shift-shares as follows.

We compute the share of trips for each taxi-zone i in week t during the years 2009, 2010 and 2011.¹⁸ We then find the average of these three values of the pre-entry period:

$$\sigma_{it} = \sum_k \sigma_{itk} / 3 \tag{2.2}$$

where σ_{itk} denotes the share of trips in taxi-zone i in week t of year $k = 2009, 2010, 2011$.

¹⁷For a more detailed discussion on shift-share instruments, we refer to two recent papers, Jaeger *et al.* (2018) and Goldsmith-Pinkham *et al.* (2018). One good example of implementation of shift-shares instruments is David *et al.* (2013)

¹⁸Recall that UberX launched in July 2012.

That is,

$$\sigma_{itk} = \frac{\text{taxi trips in zone } i \text{ in week } t \text{ of year } k}{\text{total taxi trips in NYC in week } t \text{ of year } k} \quad (2.3)$$

The reason for taking the average over three years is to smooth out the potential impact of idiosyncratic shocks in a given year. Then, the two instruments are the predicted number of Uber and Lyft trips in taxi-zone i in week t in each of the years post-entry, i.e. $y = 2014, \dots, 2017$:

$$z_{1,it} = \sigma_{it} \times UL_t \quad (2.4)$$

and the predicted number of taxi trips in taxi-zone i in week t :

$$z_{2,it} = \sigma_{it} \times Taxi_t \quad (2.5)$$

There is reason to believe that these predicted trips $z_{1,it}$ and $z_{2,it}$ are correlated with the actual trips UL_{it} and $Taxi_{it}$ respectively. Uber and Lyft drivers, either through prior experience (perhaps as a former taxi driver) or through trial and error, will figure out which locations to roam around to maximize the probability of picking up a passenger. Unless there is a significant change in economic activity across taxi-zones between the early years in our sample and the later years, zones that had a large fraction of taxi trips in 2011 will also tend to be the places which will generate a large fraction of Uber and Lyft trips in 2015. Very similar logic applies for the predicted taxi trips.

Our argument that Bartik shift-shares satisfy the assumption of exogeneity is as follows. These shift-shares are composed of two terms – total Uber/Lyft trips and total taxi trips in New York City during our sample period and intensity of taxi activity several years prior to the start of our sample period. Neither of these terms should be correlated with complaints. City-wide trips are determined by factors that

affect commuting activity in all 263 zones only a small subset of which will also affect the complaints of a single zone. Shares of trips in a single zone back in 2011 cannot reasonably be expected to be correlated with complaints in 2014.

2.5 Results

2.5.1 Full sample

We report the OLS estimates for high-frequency complaints using the full sample in Table 2.5. All six categories of complaints against taxi drivers have gone up since the arrival of Uber and Lyft. The relationships are all statistically significant at 5% or less. The coefficient for complaints by non-passengers pertaining to unsafe driving is 0.053 which indicates a rise in weekly complaints of 0.053 at the zone-level for every 1000 Uber and Lyft trips. The average number of weekly Uber and Lyft trips in a typical taxi-zone during the sample period (i.e. between 2014 and 2017) was roughly 6000 (Table 2.2). This led to an increase in unsafe driving complaints by non-passengers by $6 \times 0.053 = 0.318$ complaints per week in such a taxi-zone. An uniform increase of Uber and Lyft trips from 0 to 6,000 in all 263 taxi-zones would lead to $0.318 \times 263 = 84$ additional complaints across the city in a week. City-level coefficients reflecting the increase in complaints at the mean for the other types of complaints can be computed in a similar manner. While the magnitude of the rise in these other types of complaints are much smaller in comparison to that of unsafe driving complaints by non-passengers, they are nevertheless not negligible when considered at the city level.

Table 2.6 presents the results for the less frequent complaints. None of the estimates are statistically significant. We note here that we did not split the categories of complaints into those that increased due to competition from ride-sharing services and those that did not. Rather, we split them, as mentioned before, by frequency of occurrences. However, we are not surprised that the less frequent complaints were not

Table 2.5: High-frequency complaints, OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	unsafe_np	pick_ref	fare_tip	discourteous	route	unsafe_p
No. of Uber and Lyft Pickups (000s)	0.053** (0.021)	0.004** (0.002)	0.005*** (0.002)	0.003** (0.001)	0.003*** (0.001)	0.002** (0.001)
No of Taxi Pickups (000s)	0.026*** (0.004)	0.020*** (0.002)	0.012*** (0.002)	0.008*** (0.001)	0.004*** (0.001)	0.005*** (0.001)
Boro Pickups (000s)	-0.003 (0.006)	0.014* (0.008)	0.009** (0.004)	0.009*** (0.002)	0.000 (0.002)	0.003** (0.002)
Avg. Taxi Trip Duration (minutes)	0.000† (0.000)	0.000 (0.000)	0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)
Avg. Taxi Trip Distance (miles)	0.000*** (0.000)	-0.000*** (0.000)	0.000*** (0.000)	0.000** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
Avg. Tip per Trip	0.000 (0.000)	0.000 (0.000)	-0.001*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	-0.102 (0.139)	0.040*** (0.015)	0.118*** (0.024)	0.080*** (0.011)	0.060*** (0.010)	0.032*** (0.009)
Adjusted R^2	0.028	0.015	0.008	0.005	0.002	0.004
Increase in complaints at city-level	84	6	8	5	5	3

Standard errors in parentheses. All standard errors are clustered at the taxi-zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a taxi-zone at the week level. All columns include zone-quarter fixed effects and $N = 45,752$ in each column. Period of analysis begins at April 2014 and ends December 2017 with missing values for the months of October to December 2014. †All coefficients appearing as 0.000 are truncated to maintain consistent format. Coefficients capturing increase in complaints at city-level are rounded to whole numbers.

Table 2.6: Low-frequency complaints, OLS Estimates

	(1)	(2)	(3)	(4)	(5)
	den_req	cellphone	broken equip	unauth_pickup	unclean
No. of Uber and Lyft Pickups (000s)	0.001 (0.001)	0.000 (0.001)	-0.000 (0.001)	0.003 (0.003)	0.000 (0.000)
No of Taxi Pickups (000s)	0.006*** (0.001)	0.003*** (0.001)	0.003*** (0.000)	0.001 (0.001)	0.001** (0.000)
Boro Pickups (000s)	0.003* (0.002)	0.007*** (0.001)	0.002 (0.002)	0.006 (0.006)	-0.000 (0.001)
Average Taxi Trip Duration (minutes)	0.000† (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Average Taxi Trip Distance (miles)	-0.000*** (0.000)	-0.000 (0.000)	-0.000*** (0.000)	-0.000 (0.000)	0.000 (0.000)
Average Tip per Trip	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Constant	0.015** (0.006)	0.008 (0.006)	0.011** (0.005)	0.001 (0.012)	0.000 (0.003)
Adjusted R^2	0.004	0.002	0.002	0.001	0.001
Increase in complaints at city-level	2	0	0	5	0

Standard errors in parentheses. All standard errors are clustered at the taxi-zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a taxi-zone at the week level. All columns include zone-quarter fixed effects and $N = 45,752$ in each column. Period of analysis begins at April 2014 and ends December 2017 with missing values for the months of October to December 2014. †All coefficients appearing as 0.000 are truncated to maintain consistent format. Coefficients capturing increase in complaints at city-level are rounded to whole numbers.

Table 2.7: High-frequency complaints, IV Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	unsafe_np	pick_ref	fare_tip	discourteous	route	unsafe_p
No. of Uber and Lyft Pickups (000s)	0.069** (0.032)	-0.002 (0.003)	0.005* (0.003)	0.003 (0.002)	0.001 (0.001)	0.000 (0.001)
No. of Taxi Pickups (000s)	0.021*** (0.005)	0.025*** (0.002)	0.012*** (0.002)	0.009*** (0.001)	0.005*** (0.001)	0.006*** (0.001)
No. of Boro Pickups (000s)	-0.006 (0.008)	0.015** (0.007)	0.009** (0.004)	0.009*** (0.002)	0.000 (0.002)	0.003** (0.002)
Avg. Taxi Trip Duration (minutes)	-0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Avg. Taxi Trip Distance (miles)	0.000 (0.001)	-0.004*** (0.001)	-0.002 (0.001)	-0.000 (0.001)	-0.001* (0.001)	-0.000 (0.001)
Avg. Tip per Trip	0.000 (0.000)	0.001** (0.000)	-0.001** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Centered R^2	0.028	0.015	0.008	0.005	0.003	0.004
p-value for endogeneity test	0.386	0.001	0.747	0.531	0.072	0.154
Change in complaints at city-level‡	109	-3	8	5	2	0

Standard errors in parentheses. All standard errors are clustered at the taxi-zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a taxi-zone at the week level. All columns include zone-quarter fixed effects. $N = 45,024$ in each column. Period of analysis begins at April 2014 and ends June 2016 with missing values for the months of October to December 2014. Coefficients capturing increase in complaints at city-level are rounded to whole numbers. †All coefficients appearing as 0.000 are truncated to maintain consistent format. ‡See explanation of city-level coefficients in the discussion section.

The p-value for the Kleibergen-Paap LM test for under-identification is 0.00 and thus the null hypothesis of under-identification is rejected. The F statistic for the Kleibergen-Paap Wald test for weak identification is 191.966 and the null hypothesis of weak instruments is rejected. The endogeneity test is the Durbin-Wu-Hausman version. The null hypothesis of exogeneity of taxi trips and Uber and Lyft trips is rejected at the 5% significance level for the case of pickup refusal complaints only. First-stage regression results and related diagnostics are reported in the Appendix.

significantly affected. The high-frequency complaints are regarding behavior that usually provokes a strong response by passengers, such as driving recklessly, refusing to take the rider where he/she wants to go, rude behavior etc.. The low-frequency complaints on the other hand may bother the passenger but may not frustrate him/her enough to make a phone call to complain against the driver. For example, an unclean car or cellphone usage by the driver may not be worth the effort for many passengers to call 311 and report. From the regression results, it seems that this has continued to be the case after the arrival of Uber and Lyft. Regression results using IV estimation and for various sub-samples¹⁹ do not bring up anything different and hence from here on we will present results for high-frequency complaints only.

In Table 2.7, we show the estimates from the 2SLS regressions on high-frequency complaints. The interesting contrast between the OLS and IV results is that the size

¹⁹Results available upon request.

Table 2.8: IV estimates, by year

	(1)	(2)	(3)	(4)	(5)	(6)
	unsafe_np	pick_ref	fare_tip	discourteous	route	unsafe_p
<u>All years (N=45024)</u>						
No. of Uber and Lyft Pickups (000s)	0.069** (0.032)	-0.002 (0.003)	0.005* (0.003)	0.003 (0.002)	0.001 (0.001)	0.000 (0.001)
<u>2014-2015 (N=19309)</u>						
No. of Uber and Lyft Pickups (000s)	0.037** (0.017)	0.143*** (0.017)	0.034** (0.016)	0.036** (0.015)	0.034*** (0.010)	0.003 (0.010)
<u>2016-2017 (N=25715)</u>						
No. of Uber and Lyft Pickups (000s)	0.063** (0.029)	-0.001 (0.003)	0.006** (0.003)	0.002 (0.002)	0.001 (0.002)	0.001 (0.002)

Standard errors in parentheses. All standard errors are clustered at the taxi-zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a taxi-zone at the week level. All columns include zone-quarter fixed effects and control variables Boro Pickups, Avg. Taxi Trip Duration, Avg. Taxi Trip Distance and Avg. Tip per Trip.

of the coefficient for non-passenger unsafe driving complaints increased but the rest of the coefficients decreased. Further, unsafe driving complaints by non-passengers is also the only quality dimension that remains statistically significant at 5% or less once we control for potential reverse causality. We elaborate on this in light of our discussion on regressions on samples split by years and boroughs in the next two sections.

Among the control variables, yellow taxi trips and boro taxi trips have a statistically significant and positive relationship with complaints in most cases. But the other covariates have little or no explanatory power except in regard to pickup refusal complaints.

2.5.2 Years

It is likely that the penetration of Uber and Lyft was not uniform across years, boroughs and even taxi-zones. Further, some taxi-zones are busier than others and generate a disproportionate fraction of taxi activity and consequently complaints. Thus we analyze the relationship between competition from ride-sharing services and taxi driver behavior by splitting the samples in several different ways.

First, we look at the impact across time. We expect competition from Uber and

Lyft to have the greatest impact on taxi drivers' behavior in the early years after their entries. It would be unreasonable to expect that the shock to the transportation sector in NYC in the form of new ride providers (Uber and Lyft) will continue to have impact beyond a certain period. After a period of adjustment, whether that is through changes in driver or rider composition or changes in rider expectations or enforcement of rules by the TLC on taxi drivers, one should expect the impact to diminish after a while.

Table 2.8 presents the results split into the sample covering the first two and later two years. We also provide the estimates for the entire sample period for comparison purposes. The impact of Uber and Lyft was substantially larger in the first two years of our sample relative to the latter two years. Recall from Figure 2.1 that though Uber started operating UberX in New York City in July 2012, penetration was slow in 2012 and 2013 and rapidly increased in 2014 onward. While five of the complaint categories show a statistically significant increase in 2014 and 2015, only one remains to be significant in 2016 and 2017. Furthermore, the size of the coefficients are much smaller for five of the types of complaints in the latter period relative to the earlier period. These results also imply that the results for the entire time period between 2014 and 2017 are misleading to an extent because one fails to detect the rise in complaints in the earlier period by looking at the results for the entire period.

It is important to reiterate that all our regressions include zone-quarter fixed effects and hence variation in coefficients across years cannot be the result of time trends and other unobserved changes over the years, including changes that were heterogeneous across taxi-zones.

2.5.3 Boroughs

Recall that New York City is divided into five boroughs – Manhattan, Queens, Brooklyn, Bronx and Staten Island. Since Boro taxis introduced by TLC in 2013 were

Table 2.9: IV estimates, Manhattan vs. Other Boroughs

	(1) unsafe_np	(2) pick_ref	(3) fare_tip	(4) discourteous	(5) route	(6) unsafe_p
<u>New York City (N=19309)</u>						
No. of Uber and Lyft Pickups (000s)	0.037** (0.017)	0.143*** (0.017)	0.034** (0.016)	0.036** (0.015)	0.034*** (0.010)	0.003 (0.010)
No. of Boro Pickups (000s)	0.012 (0.008)	-0.004 (0.011)	0.001 (0.007)	0.009 (0.006)	-0.007** (0.003)	0.004 (0.003)
<u>Manhattan (N=5188)</u>						
No. of Uber and Lyft Pickups (000s)	0.038** (0.017)	0.142*** (0.017)	0.037** (0.016)	0.036** (0.015)	0.036*** (0.010)	0.006 (0.009)
No. of Boro Pickups (000s)	0.005 (0.010)	0.001 (0.021)	-0.003 (0.012)	0.012* (0.006)	-0.014*** (0.004)	0.007* (0.004)
<u>All other boroughs (N=14121)</u>						
No. of Uber and Lyft Pickups (000s)	-0.047 (0.146)	0.161** (0.065)	-0.114 (0.096)	0.004 (0.077)	-0.038 (0.072)	-0.109* (0.056)
No. of Boro Pickups (000s)	0.031 (0.029)	-0.011 (0.016)	0.029 (0.018)	0.013 (0.016)	0.010 (0.014)	0.022* (0.012)

Standard errors in parentheses. All standard errors are clustered at the taxi-zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a taxi-zone at the week level. All columns include zone-quarter fixed effects and control variables Boro Pickups, Avg. Taxi Trip Duration, Avg. Taxi Trip Distance and Avg. Tip per Trip. Period of analysis begins at April 2014 and ends December 2015 with missing values for the months of October to December 2014.

restricted to picking up passengers from all boroughs except Manhattan, we can find out whether the impact of competition from Boro taxis interacted with the competition from Uber and Lyft in unexpected ways. Moreover, Manhattan contains most of the busiest taxi-zones²⁰ and is hence likely to drive most of the results in aggregate. In Table 2.9, we present results separately for Manhattan and for all other boroughs. We also provide the estimates for the whole city for comparison purposes.

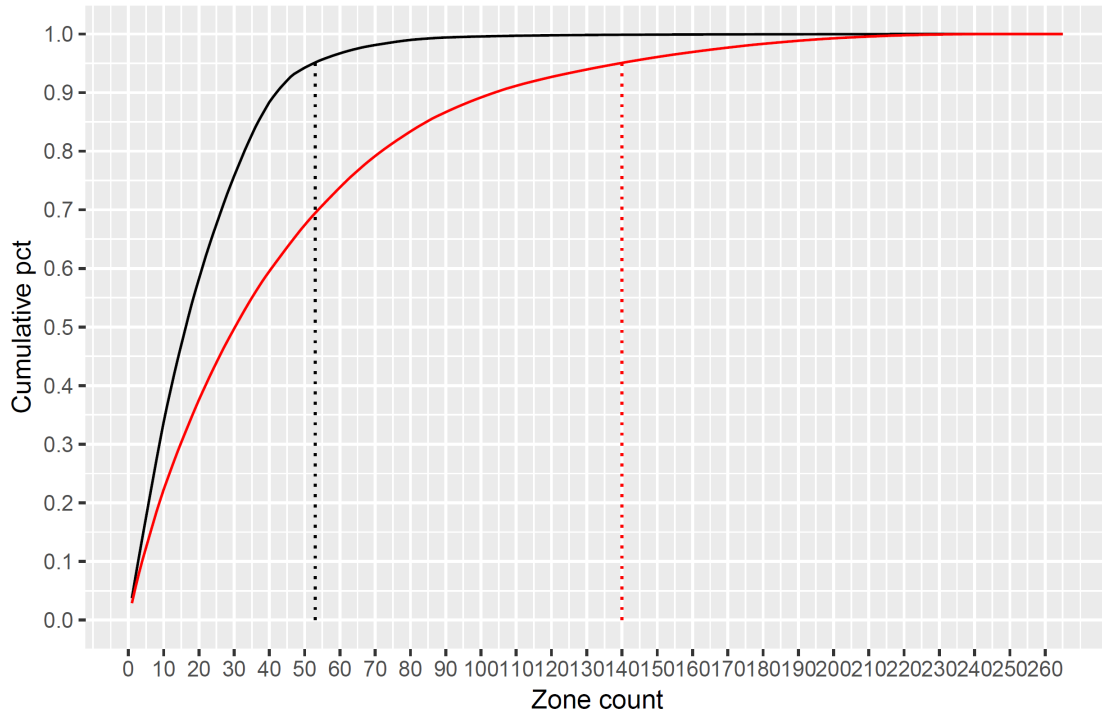
One immediately notices how similar the coefficients are for Manhattan and for the whole of New York City. The reason for driver behavior in Manhattan to mirror that of the overall city is perhaps due to the fact that most taxi activity takes place in Manhattan. This gives rise to the over-weighting of the role of the coefficients for Manhattan in determining the coefficients for the whole city.

2.5.4 Busy taxi-zones

While Manhattan dominates in taxi activity, other boroughs do contain some busy zones. For instance, both JFK and LaGuardia airports are in Queens. We plot the

²⁰The top ten busiest taxi-zones are all in Manhattan.

Figure 2.5: Cumulative sum of pick-ups (black) and complaints (red)



distributions of taxi pick-ups and complaints across taxi-zones in Figure 2.5. It shows that both distributions are highly skewed – there are 14 zones that have no complaints and 53% of zones account for 95% of all complaints. This implies that the results may vary depending on whether all taxi-zones are used for analysis or a subset of taxi-zones.

Table 2.10 provides the summary statistics for the taxi-zones that are in the top 5% in terms of taxi trips. Contrast this with the summary statistics for all zones in Table 2.2 in Section 2.2. The mean value of the number of Uber and Lyft pickups in a given zone increases from 6.09 to 23.35 (in thousands of trips) when we focus on the core zones. The number of taxi pickups are more than eight times in the core zones.

We present 2SLS regression estimates for high-frequency complaints on progressively smaller samples containing the taxi-zones that contained the highest number of trips in Table 2.11. It shows results on samples containing zones in the top 25%, top 15% and top 5% in terms of taxi trips respectively. The top two rows show the

Table 2.10: Summary Statistics – Busiest Taxi-Zones (Weekly, zone-level)

	Observations	Mean	St. Dev.	Min.	Max.
<u>All zones</u>					
No. of Uber and Lyft Pickups (000s)	45,451	6.09	9.03	0.00	68.86
No of Taxi Pickups (000s)	119,589	11.60	25.91	0.00	172.69
<u>Top 5% zones</u>					
No. of Uber and Lyft Pickups (000s)	2,545	23.35	13.82	0.20	68.86
No of Taxi Pickups (000s)	6,675	93.08	22.20	4.65	172.69

The unit of observation is taxi-zone-week. Complaints data cover the period starting January 2010 and ending December 2017. Taxi trip data start at January 2009 and end at December 2017. Uber and Lyft trip data cover the 6 months in 2014 from April to September and all of 2015, 2016 and 2017.

Table 2.11: IV estimates – sub-sample of busiest taxi-zones

	(1) unsafe_np	(2) pick_ref	(3) fare_tip	(4) discourteous	(5) route	(6) unsafe_p
<u>All taxi-zones (N=19309)</u>						
No. of Uber and Lyft Pickups (000s)	0.037** (0.017)	0.143*** (0.017)	0.034** (0.016)	0.036** (0.015)	0.034*** (0.010)	0.003 (0.010)
<u>Top 25% taxi-zones (N=5029)</u>						
No. of Uber and Lyft Pickups (000s)	0.033* (0.017)	0.141*** (0.017)	0.033** (0.016)	0.034** (0.015)	0.035*** (0.010)	0.002 (0.010)
<u>Top 15% taxi-zones (N=3092)</u>						
No. of Uber and Lyft Pickups (000s)	0.035** (0.017)	0.142*** (0.017)	0.031* (0.018)	0.030* (0.016)	0.035*** (0.011)	0.003 (0.010)
<u>Top 5% taxi-zones (N=1083)</u>						
No. of Uber and Lyft Pickups (000s)	0.019 (0.028)	0.167*** (0.023)	0.043* (0.024)	0.081*** (0.020)	0.039** (0.016)	0.016 (0.015)

Standard errors in parentheses. All standard errors are clustered at the taxi-zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a taxi-zone at the week level. All columns include zone-quarter fixed effects and control variables Boro Pickups, Avg. Taxi Trip Duration, Avg. Taxi Trip Distance and Avg. Tip per Trip. Period of analysis begins at April 2014 and ends December 2015 with missing values for the months of October to December 2014.

results for all zones for contrast.

There is evidence that complaints about pickup refusals, discourteous behavior and route taken by the driver increase after the entry of ride-sharing services, regardless of which taxi-zones we focus on. Indeed, the impact is more pronounced in the busiest taxi-zones; 0.143 increases to 0.176 in the case of pickup refusals and 0.036 more than doubles to 0.081 in the case of rude behavior.

Unsafe driving as reported by non-passengers do not have a statistically significant relationship with Uber and Lyft trips when focusing on the top 5% taxi-zones only. There is a sizable drop in the size of the coefficient from around 0.037 to 0.019. It is possibly because it is harder to drive recklessly in more congested areas. It

is interesting to note the contrast between the two sources of complaints regarding unsafe driving – from passengers and non-passengers. While the former seems to have not gone up except in the busiest areas, the reverse is true for complaints from non-passengers. This may be due to the differences in the taxi-zones. Taxi drivers spend most of their time in quieter taxi-zones driving a vacant car back to busy zones after dropping off passengers in the former zones. As a result, any unsafe driving in those less busy zones are likely to be reported by non-passengers. Moreover, given the loss in market share due to Uber and Lyft, they may have become increasingly desperate to get back to busy pickup spots and as a result engaged in reckless driving. Contrast that with driving behavior within busy zones where the likelihood of the taxi being not vacant is higher. So unsafe driving is reported by passengers at a greater frequency in these busy taxi-zones.

2.5.5 Other specifications

Given the large sample size and ease of interpretation of coefficients generated through OLS and 2SLS estimation, our preferred specification are those two. However, since complaints data is count data, it is appropriate to see how the results may vary using count data models. We present results using Poisson and Negative Binomial MLE in Table 2.12.

All coefficients in Table 2.12 are presented in the form of incident-rate ratios. A coefficient larger than 1 indicates a positive relationship between the independent and dependent variables. The absolute difference between 1 and the coefficient captures the percentage change in the number of complaints due to a change in the independent variable by one unit. For instance, in the case of route complaints, the coefficient of 1.012 indicates a 1.2% increase in the number of complaints due to an additional 1000 Uber and Lyft trips.

We make several observations in comparing these results with those using OLS in

Table 2.12: Poisson and Negative Binomial MLE estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	unsafe_np	pick_ref	fare_tip	discourteous	route	unsafe_p
<u>Poisson</u>						
Uber and Lyft Pickups (000s)	1.015*** (0.004)	1.013*** (0.005)	1.009*** (0.003)	1.008** (0.003)	1.012*** (0.005)	1.011** (0.005)
Observations	31238	28205	34069	30056	24796	19456
Log-Likelihood	-22740.900	-17517.137	-18851.077	-14594.396	-10004.598	-8392.087
<u>Negative Binomial</u>						
Uber and Lyft Pickups (000s)	1.011*** (0.003)	1.014*** (0.005)	1.010*** (0.003)	1.008*** (0.003)	1.012** (0.005)	1.011** (0.005)
Observations	31238	28205	34069	30056	24796	19456
Log-Likelihood	-22066.577	-17407.446	-18809.841	-14580.697	-9989.189	-8383.695

Standard errors in parentheses. All standard errors are clustered at the taxi-zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a taxi-zone at the week level. All columns include zone-quarter fixed effects and control variables Boro Pickups, Avg. Taxi Trip Duration, Avg. Taxi Trip Distance and Avg. Tip per Trip. All coefficients are presented in the form of incident-rate ratios. See the text for interpretation of these ratios. Period of analysis begins at April 2014 and ends December 2017 with missing values for the months of October to December 2014.

Table 2.13: OLS estimates using daily and monthly data

	(1)	(2)	(3)	(4)	(5)	(6)
	unsafe_np	pick_ref	fare_tip	discourteous	route	unsafe_p
<u>Daily data, 2014-2017, N=230614</u>						
Uber and Lyft Pickups (000s)	0.082 (0.052)	0.009 (0.007)	0.023** (0.011)	0.005 (0.007)	0.011*** (0.004)	0.005 (0.006)
<u>Daily data, 2014-2015, N=101427</u>						
Uber and Lyft Pickups (000s)	0.021 (0.052)	0.184*** (0.048)	0.015 (0.036)	0.003 (0.028)	-0.022 (0.024)	-0.010 (0.044)
<u>Daily data, 2016-2017, N=129187</u>						
Uber and Lyft Pickups (000s)	0.090 (0.063)	0.009 (0.008)	0.023* (0.012)	0.007 (0.007)	0.015*** (0.004)	0.007 (0.006)
<u>Monthly data, 2014-2017, N=9754</u>						
Uber and Lyft Pickups (000s)	0.041*** (0.012)	0.015*** (0.003)	0.008*** (0.003)	0.003 (0.003)	0.001 (0.002)	0.001 (0.002)
<u>Monthly data, 2014-2015, N=4226</u>						
Uber and Lyft Pickups (000s)	0.052*** (0.012)	0.130*** (0.011)	0.033*** (0.008)	0.019*** (0.006)	0.017*** (0.006)	0.009** (0.004)
<u>Monthly data, 2016-2017, N=5528</u>						
Uber and Lyft Pickups (000s)	0.040*** (0.014)	-0.005* (0.003)	0.003 (0.002)	0.000 (0.003)	-0.002 (0.002)	-0.000 (0.002)

Standard errors in parentheses. All standard errors are clustered at the taxi-zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a taxi-zone at the daily level in the top three sets of results and at the monthly level in the bottom three sets of results. Daily-level regressions include zone-month fixed effects and monthly-level regressions include zone-year fixed effects. All estimations include control variables Boro Pickups, Avg. Taxi Trip Duration, Avg. Taxi Trip Distance and Avg. Tip per Trip.

Table 2.5. First, all complaints have a positive and statistically significant relationship with increased competition from ride-sharing services, similar to what we found with OLS. Second, both Poisson and Negative Binomial estimation provide similar results. Third, the magnitude of the coefficients of all the complaints are smaller than those from OLS. For instance, the coefficient of 1.008 for complaints pertaining to discourteous behavior by taxi drivers translates to an increase in complaints at the city-level by 2.5.²¹ The corresponding OLS coefficient is 4.7.

Given the count nature of complaints data and the potential non-linearity in the relationship between increasing competition and complaints (it is unlikely that complaints will keep rising at the same rate as Uber/Lyft activity continues to increase; diminishing marginal effect is expected), we would prefer to use Poisson or Negative Binomial estimation as our preferred specification when correcting for endogeneity also. However, as of now, there are no established methods to estimate panel data using Poisson and Negative Binomial estimation while also using instruments variables. Hence we present non-IV results only.

Given that all our data are either at the trip or incident level, we had the option of aggregating by year, month, week, day or even hour. A question may arise regarding our selection of aggregating at the weekly level. In making this choice, we had to deal with the issue of excessive 0s in the data. Because most zones in most days do not generate any complaints, the dependent variables contain a lot of 0s which cause problems with linear estimation. In aggregating at the week (or something longer than a week), we mitigate this problem. However, in Table 2.13, we post results where the time unit is daily or monthly as opposed to weekly for contrast.

While aggregating at the monthly level lead to results similar to what we find with weekly data (see Table 2.5), daily-level aggregation leads to very different numbers.

²¹ $0.8\% \times 0.2 \times 263 \times 6$ where 0.2 is the mean number of route complaints per zone in a week (see Table 2.3), there are 263 taxi-zones and 6 represents the 6000 additional Uber/Lyft trips which is the mean number of trips in the sample.

We believe a linear specification does not capture the excessive 0s in the data well. While aggregation at the monthly level provide similar results to weekly aggregation, we prefer the latter because it allows us to use zone-quarter fixed effects as opposed to zone-year fixed effects. Since we are dealing with several possible confounding factors (see Section 2.3 above), and because quarter fixed effects absorb time-varying effects at a finer level than year fixed effects, we believe it is important to be able to control for as many of those confounding factors and at as fine a level as possible.

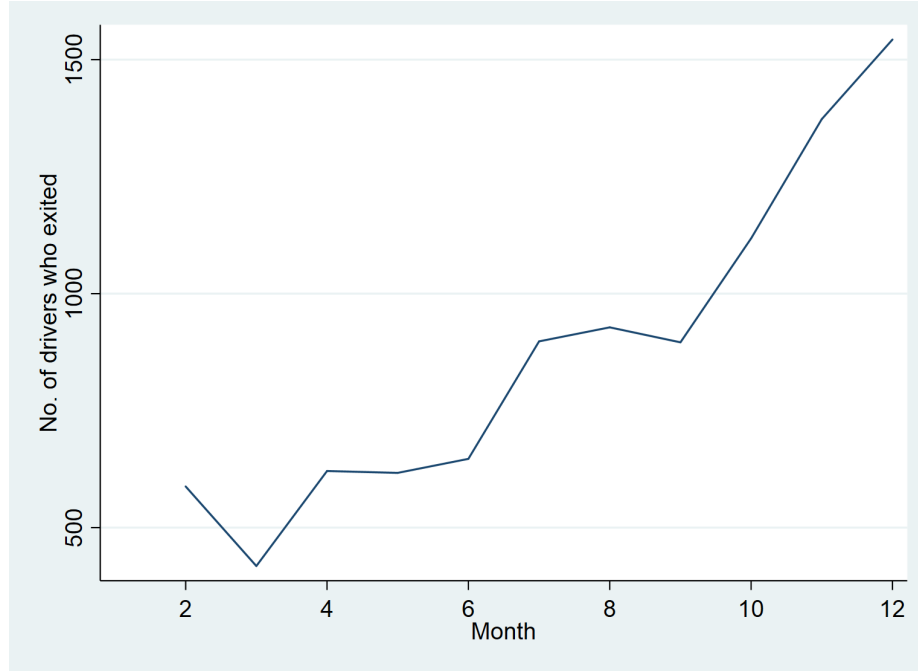
2.6 Mechanism

Our results and discussion provide a story of a connection between increased penetration by Uber and Lyft and a resulting decrease in service quality provided by taxi drivers. We want to find out what may be the mechanism linking the two. In other words, why should it be the case that service quality goes down when Uber arrives? To investigate one possible explanation, we use a different dataset of taxi trip data that contain driver information.

The first batch of NYC taxi trip data the TLC released contain medallion numbers and hack license numbers. Even though the numbers are scrambled, one can decode the numbers to find out the identity of the taxi driver with relative ease. However, this original dataset contain data for the year 2013 only; due to privacy concerns, TLC released data for later years (2014, 2015, etc.) after removing the medallion and hack license numbers entirely.

The complaints dataset that we have been using for the entirety of the paper also provide hack license numbers for most of the drivers involved in the complaints incidents. By matching the 2013 taxi trip data with 2013 complaint data, we generated a dataset of complaints and taxi trips not at the zone level but at the driver level. This is an important step up from the data that we have used for the rest of the paper because the driver is the decision-making agent and the ability to observe their

Figure 2.6: Number of drivers that left taxis in 2013, by month



behavior directly will allow us to test certain hypotheses.²²

In particular, we analyze potential relationships between three different variables – no. of complaints against individual drivers, their individual incomes and their probability of exit, i.e. leaving taxis for another profession or perhaps to drive for Uber. If Uber and Lyft did cause taxi driver incomes to fall, as is well documented in the media and the literature, lower incomes may increase the probability of exit. As Figure 2.6 shows, an increasing number of drivers have been exiting the taxi industry. It is important to determine whether the drivers who remained with taxis generate more complaints than those who exited.

In Table 2.14, we estimate the relationship between income and complaints. Coefficients for income are greater than 1 using all three estimation methods of OLS, Negative Binomial and Poisson.²³ Thus, income is positively correlated with complaints implying that high-income drivers are also the ones who have more complaints

²²Of course, it would have been ideal to have this driver-level data for all years 2013 to 2017 and not just 2013.

²³We report OLS coefficients in IRR form like we did in Table 2.12 for comparison purposes.

Table 2.14: Relationship between Income and Complaints

	(1) OLS	(2) Neg. Bin.	(3) Poisson
Monthly Driver Income	1.012*** (0.001)	1.355*** (0.060)	1.370*** (0.092)
(Squared) Monthly Driver Income	[†] 1.000*** [†] (0.000)	0.994** (0.003)	0.992* (0.004)
Monthly Trips	0.996*** (0.001)	0.950*** (0.017)	0.951* (0.026)
Observations	394306	127397	127397
Adjusted R^2	0.003		
Log-Likelihood		-35670.210	-36000.753

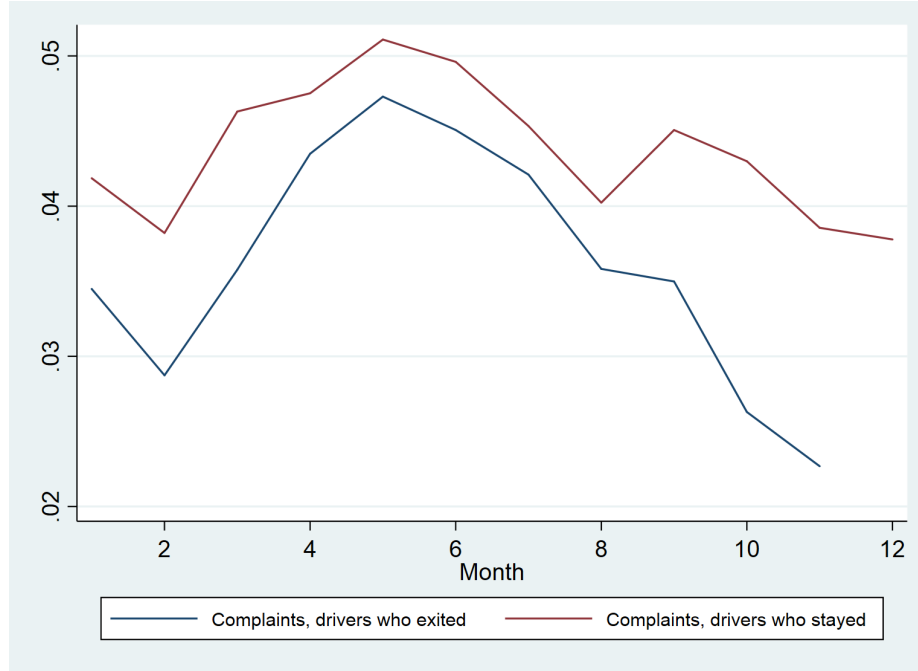
Standard errors in parentheses. Heteroskedasticity-robust standard errors are reported for OLS and Poisson estimations and bootstrapped standard errors are reported for the Negative Binomial estimation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is driver-month. All regressions include driver fixed effects. All coefficients are presented in the form of incident-rate ratios, including those of OLS, for easier comparison across regressions. [†]Truncated to maintain consistent format.

Table 2.15: Relationship between Complaints and Probability of Exit

	(1)	(2)	(3)	(4)
Yearly Complaints	-0.108*** (0.013)	0.015 (0.012)	0.066** (0.028)	0.096*** (0.029)
Yearly Driver Income		-0.022*** (0.000) [†]	-0.021*** (0.000) [†]	-0.009*** (0.002)
Complaints \times Income			-0.024** (0.012)	-0.029** (0.011)
Yearly Trips				0.005*** (0.002)
No. of months driver was active				-0.363*** (0.006)
Constant	-1.218*** (0.010)	-0.136*** (0.024)	-0.156*** (0.025)	2.611*** (0.050)
Log-Likelihood	-11381.969	-10122.998	-10120.753	-8267.750

$N = 34,425$ in all columns. Heteroskedasticity-robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is driver. [†]Truncated to maintain consistent format. Probit MLE is used in all columns. Sample includes only drivers who were active for at least 6 months in 2013.

Figure 2.7: Average no. of complaints against drivers, by month



reported against them. We will not delve into why this is so but we emphasize that we are not trying to establish causality. We also point out that since we control for trips, the positive correlation between income and complaints is not because high-income drivers drive more and hence generate more opportunities for passengers to be upset with them.

In Table 2.15, we present results from Probit regressions where the unit of observation is a driver, the dependent variable is a dummy that takes the value of 1 if the driver exited during 2013 or 0 otherwise. The independent variables are the total no. of complaints against each driver, their yearly income, trips, an interaction term of income and complaints and the no. of months each driver was active during 2013.

In Column (1), complaints is the only covariate and we observe a negative relationship indicating that a driver with more complaints against him/her have a lower probability of exit. But we have shown in Table 2.14 that income and complaints are positively correlated. Once we control for the driver's income in Column (2), we see that the sign of the coefficient for complaints reverses while the coefficient for income

is negative. This can be explained as follows. Lower income increases the probability of exit, which is as expected. But more importantly, when comparing drivers with similar incomes, those with more complaints against them have a *higher* probability of exit, which is more reasonable than what the negative coefficient for complaints in Column (1) is implying.

What is relevant to our analysis is that Uber’s negative impact on taxi driver income has led to the exit of *low*-income drivers which in turn has led to higher complaints since income and complaints are positively correlated. Figure 2.7 provides additional evidence that the drivers who left were the ones who provided better service quality. When they left and the high-complaints drivers remained, taxi service quality declined overall not necessarily because the drivers changed their behavior individually but rather the composition of the good vs. bad drivers changed.

2.7 Conclusion

The impact of platform-based businesses in general and ride-sharing services in particular has been extensive and widespread. In this paper, we look at one such impact, that of increased competition from Uber and Lyft on taxi service quality. We use a novel complaints dataset to measure (the lack of) service quality that to our knowledge has not been analyzed before. Focusing on those dimensions of quality that generate the largest numbers of complaints, we demonstrate that more competition from these ride-sharing services has affected taxi drivers’ behavior adversely. In contrast to what we would expect, which is an improvement by incumbents when new innovative challengers enter the market, we find a rise in high-frequency complaints associated with the rise of Uber and Lyft.

The results are robust to a variety of controls, including taxi drivers’ market share, a proxy for congestion and a host of fixed effects that absorb into them a variety of confounding factors. Further, we address the potential simultaneity problem in the

determination of Uber and Lyft trips, taxi trips and taxi complaints. We use well-known instruments – Bartik shift-shares – for Uber/Lyft and taxis which we argue are particularly suited to addressing simultaneity in this context. Not only do the sign and statistical significance remain similar to that of OLS, our IV estimation leads to an increase in the magnitude of the relationship between competition from Uber and Lyft and taxi drivers’ quality of service in the case of most of the high-frequency complaints we focus on.

We further provide evidence using data on individual taxi drivers that the likely cause of complaints to rise is not because they changed their behavior individually but rather because of a change in the composition of drivers. The arrival of Uber and Lyft has caused low-income drivers to leave. We show that high-income drivers tend to generate more complaints. Since these drivers remained with taxis whereas the ones who had fewer complaints against left, complaints went up overall.

Ever since the launch of Uber and Lyft, Uber and Lyft have been the subject of much policy debate and regulations, potential and actual. In August 2018, New York City imposed a cap on the number of Uber and Lyft drivers that can operate in the city.²⁴ This highlights the need for a proper understanding of whether we truly need such interventions and what are the potential consequences of such interventions.

We are cautious in assessing the policy implications of our paper, particularly regarding passenger welfare. Our results do not necessarily imply that Uber and Lyft made things worse for consumers. While taxi service quality has declined, we do not know if there has been a net gain or loss in consumer welfare. It is possible that many taxi users have switched to using ride-sharing services. If Uber and Lyft are providing a quality of service higher than taxis were providing before the arrival of these platforms, a large enough switch in riders from taxis to Uber and Lyft may have

²⁴Fitzsimmons, E. (2018, August 8) Uber Hit With Cap as New York City Takes Lead in Crackdown. *New York Times*. Retrieved from <https://www.nytimes.com/2018/08/08/nyregion/uber-vote-city-council-cap.html>

caused an *increase* in aggregate welfare. While we do not argue for or against a cap or a ban on ride-sharing services, we do point out the need to more fully understand all primary and secondary effects of such interventions.

While the results in this paper may lead to a negative view of the arrival of ride-sharing services, we should remember however that the blame should not be placed on innovative entrants when the quality provided by incumbents deteriorate. The goal of competition policy is to protect competition, not competitors. We hope that our research provides valuable information for further discussion on how to improve taxi quality in the face of competition from ride-sharing services.

2.8 Appendix

2.8.1 First Stage Regression Results

Table 2.16: First Stage Regressions

	(1)	(2)
	No. of Uber and Lyft Pickups (000s)	No. of Taxi Pickups (000s)
Predicted No. of Uber and Lyft trips (000s)	0.458*** (0.025)	0.007*** (0.002)
Predicted No. of taxi trips (000s)	0.089*** (0.008)	0.972*** (0.014)
No. of Boro Pickups (000s)	0.143*** (0.026)	-0.033** (0.016)
Avg. Taxi Trip Duration (minutes)	0.002*** (0.001)	0.001** (0.000)
Avg. Taxi Trip Distance (miles)	-0.000 (0.001)	-0.001 (0.004)
Avg. Tip per Trip	0.005*** (0.001)	-0.000 (0.001)
Observations	45024	45024
F statistic	180.7303	2659.613
F statistic p-value	0.000	0.000
S-W F statistic	2143.352	4701.789
S-W F test p-value	0.000	0.000
S-W χ^2	2151.899	4720.537
S-W χ^2 test p-value	0.000	0.000

Standard errors in parentheses. All standard errors are clustered at the taxi-zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The unit of observation is a taxi-zone at the week level. All columns include zone-quarter fixed effects. $N = 16,407$ in each column. Period of analysis begins at April 2014 and ends December 2017 with missing values for the months of October to December 2014. †All coefficients and p-values appearing as 0.000 are truncated to maintain consistent format. S-W stands for Sanderson-Windmeijer tests of under- (F test) and weak-identification (χ^2 test) of individual instruments. The null hypotheses of under-identification and weak identification are rejected for both instruments.

CHAPTER 3

UNINTENDED EFFECTS OF PRICE-MATCH GUARANTEES

3.1 Introduction

Price-match guarantees have been used by firms since at least 1947 (Edlin and Emch, 1999). Recent data show 12% of the top 500 retailers selling electronics and computers price-match, while 50% of hardware and home improvement stores and 100% of office supplies stores commit to such policies (Jiang *et al.*, 2016). More recently, brick-and-mortar stores have increasingly been price-matching online retailers.¹ To consumers, this may appear to be beneficial but economists, policymakers, and media have long debated over whether such price-matching policies are pro-competitive or anti-competitive.²

While the existing literature has demonstrated that price-match guarantees can weaken price competition, become price-discrimination devices, or signal low prices, the focus has primarily been on firm profits and consumer welfare. The impact of price-matching on firms' investment incentives and its effect on allocating production to firms relative to the social optimum has not received sufficient attention yet, which is this paper's primary theme.

We use a standard Hotelling-type model of duopoly competition between a low-cost online firm and a high-cost brick-and-mortar firm and consumers with heterogeneous preferences for online versus offline shopping. We consider timing where the

¹For example, Best Buy adopted the following price-match policy, "At the time of sale, we [Best Buy] price-match all local retail competitors (including their online prices) and we price-match products shipped from and sold by these major online retailers: Amazon.com, Bphotovideo.com, Crutchfield.com, Dell.com, HP.com, Newegg.com, and TigerDirect.com."
<https://www.bestbuy.com/site/help-topics/best-buy-price-match-guarantee/pcmcat297300050000.c?id=pcmcat297300050000> (Accessed on Jan 20, 2019.)

²See for example "Guaranteed profits: Price-match guarantees prevent rather than provoke price wars" *The Economist* 12 Feb. 2015.

brick-and-mortar firm first decides to adopt a price-match policy or not, after which the firms engage in Stackleberg price competition with the online firm moving first. We show three new unintended effects of price-match guarantees.

First, we find that investment incentives for both firms can be adversely affected due to a price-match guarantee by the high-cost offline firm. To understand why, consider the investment incentive for the high-cost firm *without* the price-match clause. When the high-cost firm does not price-match, the incentive to cut cost is affected by two channels: (i) it can expand its market share through more competitive pricing via lowered cost (extensive margin effect) and (ii) it can increase the markup per unit of sales by lowering the cost (intensive margin effect). However, with the price-match strategy in place, the high-cost firm already secures half of the market and no further market expansion is possible. Furthermore, price-matching necessitates the offline firm to fully pass on its cost reduction to consumers, which mutes the incentive through the improvement in markup. As a result, price-matching dampens the brick-and-mortar firm’s incentive to invest in cost-reduction.

We find a similar impact of price-matching on the low-cost online firm’s incentive to reduce cost. Unlike in the case of the brick-and-mortar firm implementing the price-match, the online firm benefits from a higher markup due to the price-match if it invests in cost reduction. However, the inability to gain market share due to the price-match guarantee nullifies the extensive margin effect and the overall result is the same as that of the brick-and-mortar firm—the incentive to invest in cost reduction is weakened by a price-match.

Our second main result in the paper relates to the incentive to invest in upgrading product or service quality. We augment the standard Hotelling model with quality differences in the two products offered by the duopoly firms.³ Similar to what we show in the case of distortion of cost-reduction incentives, we demonstrate that both firms

³Firms usually price-match identical items only, but the scope of differing from rivals in terms of shipping speed, in-store customer service etc. still exist.

have weaker incentives to invest in quality-enhancement with a price-match guarantee in place. The difference is that, in contrast to the cost-reduction incentive, price-matching may in some cases *increase* the incentive to invest in quality-enhancement. This is because a relative merit in quality leads to a greater extensive margin even with the price-match which is due to demand being affected by quality difference even with a price-match, which is not true in the case of symmetric quality.

Our third primary finding relates to the well-known result that in a standard Hotelling model with product differentiation, the firm with higher cost sells too large a quantity relative to the social optimum. The reason why the low-cost firm sells too few units in the Hotelling model is that when products are differentiated, the cost advantage does not lead to a market share increase at *full* strength and thus some loss of production efficiency is inevitable. Consumers' relative preferences for products cause frictions in that it prevents a low-cost producer from securing a larger market share. To worsen this problem, price-matching has an effect of diluting the benefit of having a competitive advantage in the relative cost. Hence, production inefficiency arises in a less restrictive environment under price-matching; the exception is when the price-matching firm's product has a substantial quality superiority so that the market split favors the societal outcome.

Our research reveals more reasons to suspect that the seemingly pro-competitive price matching by many offline rivals to online sellers may have hidden social costs. These hidden social costs may be important for policy evaluation over this common business practice.

3.1.1 Related literature

The early literature on price-matching emphasized the anti-competitive aspect of this practice. One plausible reason why a firm adopts a price-match policy is that it sends a message to its rivals that they will not be able to increase sales by cutting price

because the former will match that price and prevent buyers from switching. As long as a firm can make such a promise credible, for instance by putting up a written notice in its store or website, it ties itself to matching lower prices even in cases where it is harmful to the firm. Given the credibility of the threat, firms move towards an outcome of tacit collusion where they charge a price higher than they could have in a non-cooperative outcome. In short, price-match policies can be anti-competitive. This idea was first put forward by Hay, 1982 and Salop (1986) although Cooper (1986)⁴ had earlier pointed out a similar effect of most-favored-customer clauses.⁵ Our paper is similar to this early strand in that firms price-match in equilibrium by having equal *posted* prices, obviating the need for consumers to invoke the price-match clause in equilibrium.

In contrast to the anti-competitive argument, it is easy to see why price-match policies may benefit consumers. For example, if a buyer can get the lowest price at the store closest to him by showing proof of a lower price at a store farther out from his home, this saves him the trouble of a longer trip. Similarly, if he finds something cheaper online but does not want to wait for the item to arrive, he can immediately go to the local brick-and-mortar store that price-matches and get the item at the lower online price. In addition, it is known that price-matching policies can be pro-competitive if firms can adopt price-matching guarantees *and* price-beating guarantees. There are no *a priori* reasons to preclude this given the lack of legal barriers against either practice. This may allow a firm to post a price higher than those of rivals and then offer to beat the rivals' lower price by a certain amount. As long as the rivals are price-matching *posted* prices, consumers cannot invoke the price-match with rivals since the posted price of the firm with the price-beating policy

⁴The working paper version of Cooper's paper is from 1981.

⁵Most-favored-customer clauses promise customers a refund of the price difference in case a firm lowers price after the buyer purchases the item. In essence, the firm matches its *own* future price rather than that of rivals. It has very similar potential implications for facilitating collusion. We further discuss most-favored-customer clauses in Section 3.7.

is higher. Meanwhile, the price-beating firm lures customers away from the rivals by cutting *actual* prices below its rivals. This will lead to the rivals adopting the same price-beating policy which in turn leads to non-collusive Bertrand price competition (Corts, 1997; Hviid and Shaffer (1994)). However, Edlin (1997), Kaplan (2000) and Arbatskaya *et al.* (2004) argue that tacit collusion is restored when firms match both advertised and effective selling prices. Arbatskaya *et al.* (2006) provide data to show that in some cases firms do price-match actual prices on top of advertised prices.

While tacit collusion has been the dominant theme to explain price-matching, more recent literature has emphasized a different reason why firms price-match. Moorthy and Winter (2006) and Moorthy and Zhang (2006) argue that in a duopoly with asymmetric costs, the low-cost firm uses a price-match guarantee to “signal” to uninformed consumers its low-price advantage over the high-cost rival. They go on to show why the high-cost rival will not find it in its interest to also adopt a price-match guarantee. This lack of incentive ensures only the low-cost firm price-matches and the signaling mechanism works in equilibrium to aid buyers identify the low-cost from the high-cost firm. The issue with this narrative is the fact that high-cost brick-and-mortar firms are increasingly adopting price-match policies that specifically match prices of low-cost online firms. Because our model does not depend on consumers to be informed about lower prices to benefit from the price-match guarantee since it is the firm that takes up that burden, the need for signaling is moot. Hence we show that it is the high-cost firm that adopts price-matching and not the low-cost firm. The intuition is that the high-cost firm is more in need of inducing a collusive outcome with higher prices to be able to cover its higher costs in contrast to the low-cost firm.

The empirical literature on price-matching provides evidence both for and against such guarantees facilitating collusion. Grether and Plott (1984) find experiment evidence that prices are significantly higher with adoption of most-favored-customer clauses, which as we have mentioned earlier, potentially impact the incentives for

tacit collusion in a way similar to price-matching. Hess and Gerstner (1991) finds evidence specifically for price-matching. More recent work include that of Arbatskaya *et al.* (2000), Arbatskaya, 2001 and Arbatskaya *et al.* (2006) which provide mixed results regarding tacit collusion. Mañez (2006) finds that supermarkets used price-matching to signal low prices, favoring the theory of Moorthy and Winter, 2006 and against collusion. Jain and Srivastava (2000) and Srivastava and Lurie, 2001 find similar results in experiments in favor of price-matching as low-price-signals. Cabral *et al.* (2018) offer a simple model in which price matching guarantees can be a collusion-facilitating practice and present its empirical evidence using the Shell network of gas stations in Germany. One paper that most closely addresses the context we follow is by Zhuo (2017). Using prices on online retailer Amazon before and after announcements of price-match guarantees by traditional brick-and-mortar stores such as Walmart and Target, she finds that Amazon prices rose after such announcements.

Our paper is related to Edlin and Emch (1999) in that they show welfare losses arising not just due to higher prices as a result of price-matching, but over time these higher prices induce excessive entry by firms which generate further welfare losses. Our work is complementary to theirs. Instead of looking at firm entry and exit, we attempt to uncover unintended effects of price-matching practices on investments and production efficiency.

In terms of a theoretical framework, our model is similar to that of Logan and Lutter, 1989 who considered differentiated product duopoly markets with asymmetric costs. They find that the ability of price-match policies to sustain collusive prices depends on whether the high-cost firm chooses to price-match. If the firms' costs are very different, the high-cost does not price-match and pricing is competitive. On the other hand, if the firms' costs are similar, the high-cost firm price-matches and pricing is above the competitive level. While we uses a similar model to Logan and Lutter (1989), we address very different questions to uncover new effects of price-matches.

3.2 Equilibrium analysis of price-match guarantees

3.2.1 Model

We consider the standard Hotelling model of a duopoly. A continuum of consumers, whose mass is normalized to one, are uniformly distributed over the linear city $[0, 1]$. Each consumer has a unit demand. A brick-and-mortar seller, firm B, at the left corner ($x = 0$) and an online seller, firm O, at the right corner ($x = 1$) compete in prices. A consumer closer to firm B has a stronger preference toward offline shopping relative to online shopping. Heterogeneous preferences regarding online vs. offline shopping may be attributed to different patience levels in waiting for an item to arrive from the online seller, the different utility of shopping online such as saving of time, less compulsive spending, no crowds relative to the inconvenience of the inability to physically examine before purchasing items, concerns about online scams and online privacy or security. The typical transport cost parameter t measures the degree of the consumers' relative preference intensity regarding the two different modes of shopping.

Firm B's cost of serving one consumer is $c \in R_+$ whereas firm O's is normalized to zero. We motivate the assumption of asymmetric costs by using the example of online vs. brick-and-mortar firms. It is generally true that online firms locate warehouses in remote areas with lower costs which allows for carrying much greater inventory and for greater economies of scale. The need to bring in customers constrains brick-and-mortar retail stores to locate in high-traffic areas and hence they face a cost disadvantage. Moreover, often online retailers operate marketplaces allowing them to offer goods through third-party sellers and which further reduces costs by eliminating the need to carry inventory.⁶ A particular trend since online shopping became main-

⁶While throughout the paper we use the online vs. offline example, our results naturally extend to cases where there is cost asymmetry between firms due to factors other than those that differentiate online and brick-and-mortar firms. The implications of cost asymmetry are important for our results, but the reason for the asymmetry is not.

stream has been the closure of brick-and-mortar firms, big and small, as they failed to compete with online firms with a cost advantage such as Amazon.⁷

We assume that the market is fully covered and thus each firm is not a local monopoly. The timing of the game between the two firms is as follows. At the initial node firm B decides whether to price-match or not. While in reality the online firm may price-match as well, only a few online-only sellers such as eBay and NewEgg offer price-match guarantees. Hence, we opted to study the case of the brick-and-mortar firm adopting a price-match, which has become far more common lately.

We assume the decision to price-match or not is irrevocable. The sequence of deciding first to price-match or not and then choosing prices is reasonable, since firms change prices frequently whereas they tend to stick to price-matching (or not) for a longer period. The proposed timing also justifies our assumption of irrevocability as long as the duration of the game we study is shorter or equal to the period during which a firm does not change its price-matching policy.

In the subgame in which firm B does not choose to price-match, we consider the sequential-move game⁸ in which firm O acts as the price leader and firm B the follower. In the subgame following firm B deciding to price-match, firm B's choice of price following firm O's choice is automatic and trivial. The analysis proceeds backward from the two subgames following the brick-and-mortar firm's commitment decision. The equilibrium concept is subgame-perfect Nash Equilibrium.

3.2.2 No price-match subgame

Consider the subgame ensuing from firm B's choice not to price-match. We characterize the demand for each firm by identifying the indifferent consumer's loca-

⁷See for example Evangelista, Benny. "How 'Amazon factor' killed retailers like Borders, Circuit City," *SFGATE* July 14, 2015. <https://www.sfgate.com/business/article/How-Amazon-factor-killed-retailers-like-6378619.php>

⁸In the Online Appendix, we show that price-matching does not arise in a pure-strategy Nash equilibrium in the simultaneous-move game.

tion $x = \frac{1}{2} + \frac{p_O - p_B}{2t}$, which gives the demand for B, $Q_B(p_B, p_O) = x$, and for O, $Q_O(p_B, p_O) = 1 - x$. The notation is self-explanatory: p_B and p_O are respectively B's price and O's price and Q_B and Q_O are demands. We start with B's profit maximization problem: $\max_{p_B} \pi_B = (p_B - c)Q_B$ which renders the following best response function of $p_B(p_O) = \frac{1}{2}(t + p_O + c)$. Firm B's best-response plays the role of a constraint in firm O's optimization problem:

$$\max_{p_O} p_O \left(\frac{1}{2} + \frac{p_B - p_O}{2t} \right) \text{ s.t. } p_B = \frac{1}{2}(t + p_O + c).$$

Solving this problem, we derive the prices as follows:

$$p_O^* = \frac{3t + c}{2} \text{ and } p_B^* = \frac{5t + 3c}{4} \quad (3.1)$$

which yields the location of the marginal consumer $x^* = \frac{5}{8} - \frac{c}{8t}$.

In theory, there are two different cases depending on the primitive parameters c and t . If $c \leq t$, then firm B's price is lower than firm O's, $p_O^* \geq p_B^*$, where the equality holds for $c = t$. In this case consumers find no need to claim the price-match—even if firm B committed to such a policy—as they find the online price is higher than the offline price. In contrast, if the offline firm's cost disadvantage is large enough such that $c > t$, then $p_O^* < p_B^*$. Let us assume $c > t$ for subsequent analyses to ensure that the offline's marginal cost is not so low that its price-match becomes irrelevant for subsequent price competition.

In the absence of firm B's price-match, the pair of prices in (3.1) constitute the equilibrium prices. Each firm's profit is computed as

$$\pi_B^* = x^* (p_B^* - c) = \frac{(5t - c)^2}{32t} \text{ and } \pi_O^* = (1 - x^*) p_O^* = \frac{(3t + c)^2}{16t} \quad (3.2)$$

For firm B to gain a positive market share (i.e. $x^* > 0$), we need $c < 5t$. Additionally,

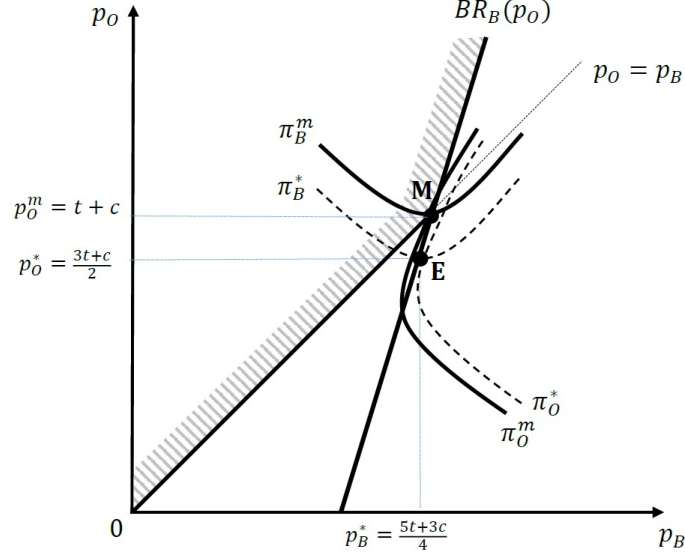


Figure 3.1: Best-response and isoprofit functions with and without price-match

the full market coverage requires $v - tx^* - p_B^* \geq 0$, which is simplified as $v \geq \frac{15}{8}t + \frac{5}{8}c$.

This outcome would occur at point E in Figure 1.

3.2.3 Price-match subgame

In the presence of the price-match commitment, the online seller's price choice is bounded by a convex set composed of a 45-degree line from the origin to point M and then follows BR_B beyond point M; the relevant edges are shaded. Firm O obtains its highest profit when its iso-profit curve passes through point M. Hence, the equilibrium prices are determined at the intersection of $p_O = p_B$ and $p_B = \frac{1}{2}(t + p_O + c)$, which gives

$$p_B^m = p_O^m = t + c \quad (3.3)$$

where the subscript m again indicates the price-match in consideration. At equal prices, each firm's profit is computed as

$$\pi_B^m = x^m (p_B^m - c) = \frac{t}{2}; \quad \pi_O^m = (1 - x^m) p_O^m = \frac{t + c}{2} \quad (3.4)$$

where $x^m = \frac{1}{2}$. The sufficient condition for full market coverage is $v - tx^m - p^m \geq 0$, which is simplified as $v \geq \frac{3}{2}t + c$ and which subsumes $v \geq \frac{15}{8}t + \frac{5}{8}c$ for $c \geq t$.

But note that we need to check when both firms do not deviate from the given price, $p^m = t + c$. Suppose that the online firm attempts to monopolize the market by deviating to $p_O^d = c - t$ so that the least interested consumer at $x = 0$ would prefer buying from firm O to buying from firm B even if firm B follows and sets its most competitive price, c . Then, firm O's deviation payoff would be $\pi_O^d = c - t$. Thus, no deviation requires $\pi_O^d \leq \pi_O^m \Leftrightarrow c - t \leq \frac{t+c}{2}$, we have $c \leq 3t$.

3.2.4 Price-match or not

For the price-match decision, throughout this paper we consider the following set of parameters:

Assumption 4. $v > \frac{3}{2}t + c$ and $c \in [t, 3t]$

Since firm B's price-match decision depends on the relative size of the continuation payoffs π_B^* and π_B^m , we can say that the price-match will be chosen if

$$\pi_B^m - \pi_B^* = \frac{t}{2} - \frac{(5t - c)^2}{32t} = \frac{(c - t)(9t - c)}{32t} > 0 \quad (3.5)$$

which is satisfied under Assumption 4. Graphically, it is clear from Figure 3.1 that firm B's isoprofit curve passing through point M is above the one passing through point E.

In summary, under Assumption 4, the subgame perfect Nash equilibrium of the sequential pricing is characterized by the path on the price-match. The equilibrium prices and payoffs are given by (3.3) and (3.4).

3.3 Static effects of price-matching

Having characterized the equilibrium in which a brick-and-mortar firm with a cost disadvantage finds it better to adopt the price-match guarantees, we show how the price-match guarantees affect the online rival, consumers and social welfare though these static effects do not constitute our main research results.

3.3.1 Effect on online rival

How would the price-match guarantees adopted by the offline seller affect its online rival? The impact on firm O can be examined by studying how firm O's payoff changes with the price-match compared to that without it. First of all, let us recall the standard result, which is obtained in our model as well, that a price-match commitment can soften price competition. Under Assumption 4, price-matching increases equilibrium prices relative to no price-match prices:

$$p_O^m - p_O^* = \frac{1}{2}(c - t) > 0; \quad p_B^m - p_B^* = \frac{1}{4}(c - t) > 0.$$

However, the higher prices do not necessarily imply that the online seller also benefits from weakened competition. The comparison between firm O's payoff with the price-match and without it can be decomposed into two opposing forces:

$$\begin{aligned} \pi_O^m - \pi_O^* &= \underbrace{(p_O^m - p_O^*) Q_O^m}_{\text{mark-up effect (+)}} + \underbrace{p_O^* (Q_O^m - Q_O^*)}_{\text{market-share effect (-)}} \\ &= \frac{(c - t)}{4} - \frac{(c + 3t)(c - t)}{16t} = -\frac{(c - t)^2}{16t} < 0 \end{aligned}$$

On the one hand, firm B's price-match weakens price competition, which makes firm O enjoy a higher per-unit markup on existing sales, captured by the first term on the right-hand side of the equation above. On the other hand, firm O loses market

share due to the price-match policy, represented by the second term above. We find that price-matching makes the online seller earn *less* profit because the negative market-share effect outweighs the positive mark-up effect. Graphically, it is clear from Figure 3.1 that firm B's isoprofit curve passing through point M is to the left of the one passing through point E.

3.3.2 Effect on consumers

Antitrust concerns are usually focused more on the impact on consumers than on rivals. We showed that equilibrium prices increase due to price-matching. Does this necessarily imply that *all* consumers will be worse off? To answer this question, let us start by noticing that there are three groups of consumers who are affected by a price-match guarantee differently based on their location. First, consumers located close to firm B in $x \in [0, \frac{5}{8} - \frac{c}{8t})$ buy from firm B regardless of price-matching. These buyers are worse off because $p_B^m > p_B^*$. Similarly, the consumers located in $x \in [\frac{1}{2}, 1]$ always buy from firm O and they also become worse off because $p_O^m - p_O^* > 0$. In contrast, consumers in the region $x \in [\frac{5}{8} - \frac{c}{8t}, \frac{1}{2})$ would have bought from firm O without the price-match but switch to firm B in the presence of the price-match. Hence, the net surplus of a consumer x in this group is computed as $V^*(p_O^*, x) = v - t(1 - x) - (\frac{3t+c}{2})$ under no price-match and $V^m(p_B^m, x) = v - tx - (t + c)$ under the price-match guarantees. The net change in consumer surplus denoted by $\Delta V(x)$ is given by

$$\Delta V(x) \equiv V^m(p_B^m, x) - V^*(p_O^*, x) = \underbrace{-\frac{1}{2}(c - t)}_{\text{price effect (-)}} + \underbrace{t(1 - 2x)}_{\text{preference effect (+)}} \quad (3.6)$$

A consumer switching due to the price-match ends up paying the higher price $p_B^m = t + c$ compared to $p_O^* = \frac{3t+c}{2}$ without the price-match. The first term in (3.6) captures this negative price effect. However, this switching consumer now saves on “travel

costs” by choosing a more preferred mode of shopping given equal prices by both firms. The second term measures this positive preference effect. Note that $\Delta V(x)$ decreases with x because the price effect is independent of x , but the preference effect decreases with x . The largest preference effect occurs for the consumer located at $x^* = \frac{5}{8} - \frac{c}{8t}$ (and there is no preference effect for $x = 1/2$). But we can verify that even this consumer finds the price-match undesirable, i.e., $\Delta V\left(\frac{5}{8} - \frac{c}{8t}\right) = -\frac{1}{4}(c - t) < 0$ which ensures $\Delta V(x) < 0$ for every switching consumer. That is, $\Delta V(x) < 0$ for $\forall x \in [\frac{5}{8} - \frac{c}{8t}, \frac{1}{2})$.

The total consumer surplus denoted by S is computed from aggregating all consumers’ net surplus.⁹ With the price-match, it is given by

$$S^m = \int_0^{1/2} (v - tx - p_B^m)dx + \int_{1/2}^1 (v - t(1 - x) - p_O^m)dx = v - \frac{5}{4}t - c.$$

Without the price-match, the aggregate consumer surplus is

$$S^* = \int_0^{x^*} (v - tx - p_B^*)dx + \int_{x^*}^1 (v - t(1 - x) - p_O^*)dx = v - \frac{103}{64}t - \frac{21}{32}c + \frac{c^2}{64t}$$

where $x^* = \frac{5}{8} - \frac{c}{8t}$. The difference in aggregate consumer surplus due to the price-match is

$$\Delta S = S^m - S^* = -\frac{(c - t)(c + 23t)}{64t} < 0$$

which verifies that price-matching leads to a decrease in consumer surplus as every consumer is worse off from the higher prices due to the price-match policy and she is not sufficiently compensated for the loss by a positive preference effect.

⁹Note that we use S for consumer surplus and later use W for social welfare.

3.3.3 Effect on social welfare

Since total welfare is the sum of firm profits and consumer surplus, the welfare effects of price-matching are consistent with what we have described regarding firm profits and consumer surplus. One notable point is how the change in firm B's profit due to the price-match is substantial relative to the impact on its rival and consumers.

Using prior results, we can obtain the welfare with and without price-match as follows: $W^m = \pi_B^m + \pi_O^m + CS^m$ and $W^* = \pi_B^* + \pi_O^* + CS^*$ from which the net change in welfare is given by

$$\Delta W \equiv W^m - W^* = -\frac{(c-t)(7c+t)}{64t} < 0. \quad (3.7)$$

The offline seller's gain is not enough to offset the loss to consumers and the decrease in online rival's profits. We summarize our results in the following proposition:

Proposition 6. *Under Assumption 4, the price-match guarantees have the effects, compared to the no price-match benchmark, that (i) the online firm is worse off, and (ii) each consumer receives smaller net surplus, and thus social welfare decreases.*

3.4 The incentive to invest in cost reduction

Here we extend the baseline model to discuss unintended effects of price-match guarantees. How would price-matching affect the incentive of the brick-and-mortar seller to reduce its marginal cost, equivalently its cost disadvantage c ? What about the incentive of the online seller to widen the cost advantage? To address these questions, we add a new stage to the timing of the game. Let either firm make investments *after* firm B's decision to offer a price-match guarantee but *before* price competition. We could explicitly model investment cost functions, but our analysis does not make it imperative. This is because essentially we end up comparing the marginal benefit of such investments with the price-match and without it, which means the marginal

cost of investment is not crucial for analysis, unless if we were specifically interested in the optimal choice of investment level. Instead we assume a one-time fixed cost F of investing in the cost-reduction technology and that the size of F does not depend on whether a price-match guarantee is offered or not.

3.4.1 Incentive for firm B

Consider first the investment incentive for firm B. Using the equilibrium payoffs we had earlier derived and after subtracting fixed cost F , we have $\pi_B^m = \frac{t}{2} - F$ and $\pi_B^* = \frac{(5t-c)^2}{32t} - F$. With price-matching, the marginal change in firm B's profit in response to a marginal decrease in its cost disadvantage is given by

$$-\frac{d\pi_B^m}{dc} = \underbrace{x^m \left(1 - \frac{\partial p_B^m}{\partial c}\right)}_{\text{intensive margin effect} = 0} + \underbrace{(p_B^m - c) \left(-\frac{\partial x^m}{\partial c}\right)}_{\text{extensive margin effect} = 0} = 0. \quad (3.8)$$

The first term in (3.8) measures the effect of a reduction in cost on the mark-up for each unit of existing sales. A decrease in the marginal cost by a dollar means an increase in profit due to the improved per-unit mark-up; however, its effect on the price is given by $\frac{\partial p_B^m}{\partial c}$. Recalling that $p_B^m = t + c$, the price goes up by the exact same amount. The two effects, the change in cost and the change in price, are exactly offset.¹⁰ The second term in (3.8) measures the extensive margin effect, which arises via a change in the market share. Under the price-match guarantee, the extensive margin does not change because the firms must necessarily split the market in half at equal prices.¹¹ In sum, we find both the intensive and extensive effects to be null, which leads to $\frac{d\pi_B^m}{dc} = 0$. Firm B has no incentive to invest in cost-reduction under

¹⁰This is unique to the uniform distribution and in theory the intensive margin effect may go either way if other distributions are used to model consumer preferences.

¹¹This is driven by the assumption in the Hotelling model that total market size is constant. We thank Keisuke Hattori for this observation. Hence our results are limited to cases where, for some reason, no further market expansion is possible. We can use the 'hinterland' model to extend our analysis to cases where market expansion is possible, but we do not pursue it here and leave it for future research.

price-matching.

Next, we analyze firm B's investment incentive following no price-match in a similar manner:

$$-\frac{d\pi_B^*}{dc} = \underbrace{x^* \left(1 - \frac{\partial p_B^*}{\partial c}\right)}_{\text{intensive margin effect} > 0} + \underbrace{(p_B^* - c) \left(-\frac{\partial x^*}{\partial c}\right)}_{\text{extensive margin effect} > 0} = \frac{5t - c}{16t} > 0 \quad (3.9)$$

In contrast to the case of price-matching, there is a positive intensive margin effect without price-matching. The lower cost improves the mark-up since the market price does not increase as much as with a price-match, i.e. one-to-one. In addition, the cost-reduction has a positive effect on the extensive margin for firm B. With both intensive and extensive margin effects being positive, firm B has a greater incentive to invest to reduce cost in a no-price-match regime.

Proposition 7. *Under Assumption 4, price-matching by the high-cost firm weakens its incentive to reduce its cost disadvantage.*

3.4.2 Incentive for firm O

We apply an analogous analysis for the online firm's investment to expand its cost advantage by *raising* c .¹² Firm O's equilibrium payoffs are $\pi_O^m = \frac{t+c}{2} - F$ with price-matching and $\pi_O^* = \frac{(3t+c)^2}{16t} - F$ without. Recalling that $p_O^m = t + c$ and $1 - x^m = \frac{1}{2}$, the change in profit in response to a one-dollar increase in c under price-matching is given by

$$\frac{d\pi_O^m}{dc} = \underbrace{(1 - x^m) \frac{\partial p_O^m}{\partial c}}_{\text{intensive margin effect} > 0} + \underbrace{p_O^m \left(-\frac{\partial x^m}{\partial c}\right)}_{\text{extensive margin effect} = 0} = \frac{1}{2}. \quad (3.10)$$

¹²Recall that for simplicity in analysis, we opted to include the single cost parameter c to reflect the asymmetry in cost between the two firms instead of two separate cost parameters. In that sense, firm O raising c is equivalent to firm O investing in its own cost reduction.

Given $p_O^* = \frac{3t+c}{2}$ and $1 - x^* = 1 - \frac{5t-c}{8t}$, firm O's investment incentive without price-matching is characterized by

$$\frac{d\pi_O^*}{dc} = (1 - x^*) \frac{\partial p_O^*}{\partial c} + p_O^* \frac{\partial(1 - x^*)}{\partial c} = \frac{3t + c}{8t} \quad (3.11)$$

Since $\frac{3t+c}{8t} > \frac{1}{2}$, firm O's incentive to invest in cost-reduction is weakened like in the case of firm B. However, to see why this is the case, we again look at the intensive and extensive margin effects with and without price-matching. Price-matching eliminates the extensive margin effect just as in the case of firm B (see Footnote 10) whereas it is possible for firm O to snatch market share away from firm B by reducing cost when there is no price-matching. Unlike in the case of firm B however, the intensive margin effect with price-matching is positive and greater than that without price-matching ($\frac{1}{2}(\frac{3}{8} + \frac{c}{8t}) > \frac{1}{2}$ under Assumption 4). The net effect remains stronger without price-matching nevertheless. This implies that, under a price-match, the inability to gain market share outweighs any gains from a higher markup due to a bigger cost advantage.

Proposition 8. *Under Assumption 4, price-matching by the high-cost firm weakens the low-cost firm's incentive to increase its cost advantage.*

3.5 The incentive to invest in upgrading quality

So far we have assumed that the two firms offer products identical in quality, i.e., $v_B = v_O = v$. But the online and offline firms may differ in their other features such as warranty, shipping, or return policies. For instance, brick-and-mortar stores may try to enhance in-store services by hiring more staff and offering pick-up services for online orders. We introducing a quality difference to analyze the impact of price-matching on either firms' incentive to invest in upgrading such quality dimensions like shipping speed.

Define $\alpha = v_O - v_B$. Then, α denotes the online firm's quality superiority if $\alpha > 0$ or its quality inferiority for $\alpha < 0$, and $\alpha = 0$ representing the special case of same quality that we have used in our prior analyses. Usually a cost reduction is a mirror image to a quality improvement, and *vice versa*. However, this general intuition may not hold in our model. This is because the change in the quality difference α affects the equilibrium market demand under price-match, which is not the case with changes in the cost difference c . Building on this insight, we analyze firm B's incentive to decrease α and firm O's incentive to increase α . Since the derivation procedures are similar to those in the basic model, we skip them. However, with the presence of α , we need a revised version of the full coverage market assumption ($x^* > 0$) and the range of values of c in which price-matching arises in equilibrium:

Assumption 5. $v_B \geq \frac{3}{2}t + c - \frac{3}{2}\alpha$ and $c \in [t + \frac{5}{3}\alpha, 3t + \alpha]$ and $t \geq 3\alpha$.

Note that for $\alpha = 0$, Assumption 5 collapses to Assumption 4.

3.5.1 Incentive for firm B

We proceed to analyzing firm B's incentive to lower its quality inferiority. Given $x^m(\alpha) = \frac{t-\alpha}{2t}$ and $p_B^m(\alpha) = t + c - \alpha$,

$$-\frac{d\pi_B^m(\alpha)}{d\alpha} = \underbrace{x^m(\alpha) \left(1 - \frac{\partial p_B^m(\alpha)}{\partial \alpha}\right)}_{\text{intensive margin effect} > 0} + \underbrace{(p_B^m(\alpha) - c)(-x^{m'}(\alpha))}_{\text{extensive margin effect} > 0} = \frac{t - \alpha}{t}. \quad (3.12)$$

Note that firm B's market share under price-matching is a function of the quality difference parameter α . As a result, the marginal effect of a quality-enhancing investment on market share is no longer zero, i.e., $-x^{m'}(\alpha) = \frac{1}{2t} > 0$. In contrast, market share is *not* a function of the cost parameter c and hence any cost reduction has no impact. With a price-match guarantee, firm B's investment incentive is measured by $-\frac{d\pi_B^m(\alpha)}{d\alpha}$. The condition for a weakening of investment incentive under price-matching

is characterized by $\left| \frac{d\pi_B^*(\alpha)}{d\alpha} \right| > \left| \frac{d\pi_B^m(\alpha)}{d\alpha} \right|$, which yields the following parametric condition:

$$\alpha > \frac{1}{11}(t + 3c) \equiv \bar{\alpha}_B. \quad (3.13)$$

That is, if firm O's quality superiority is large enough, price-matching leads to a lower incentive for the brick-and-mortar firm B to invest in upgrading quality. Otherwise, price-matching increases firm B's motivation to enhance quality. This is because as we mentioned above the extensive margin effect turns out positive under the price-match, which was not the case when we studied cost-reducing investment.

Proposition 9. *Under Assumption 5, price-matching weakens the brick-and-mortar firm's incentive to invest in quality-improvement if $\alpha > \bar{\alpha}_B$, but strengthens it otherwise.*

3.5.2 Incentive for firm O

We can examine firm O's incentive to improve quality in a similar manner. The intuition applied to the online firm is the same – the extensive margin effect is no longer zero even with price-matching. Firm B's incentive to enhance quality is weakened with a price-match guarantee if $\left| \frac{d\pi_O^*(\alpha)}{d\alpha} \right| > \left| \frac{d\pi_O^m(\alpha)}{d\alpha} \right|$, which is simplified as

$$\alpha > \frac{2}{3}(c - 3t) \equiv \bar{\alpha}_O. \quad (3.14)$$

Price-match guarantees decreases firm O's incentive to invest in quality if its quality is sufficiently superior, i.e. $\alpha > \bar{\alpha}_O$. However, in contrast to the investment incentives in the cost-reduction case, if firm O's product is either inferior or not sufficiently superior, price-matching strengthens firm O's incentive to upgrade quality.

Proposition 10. *Under Assumption 5, price-matching weakens the brick-and-mortar firm's incentive to invest in quality-improvement if $\alpha > \bar{\alpha}_O$, but strengthens it otherwise.*

3.6 Production inefficiency of price-matching

In this section, we examine the effect of price-matching on the well-known result of production inefficiency in the standard Hotelling model with asymmetric costs – the firm with the higher cost sells too large a quantity relative to the social optimum.¹³ The reason why the low-cost firm sells too few units in the Hotelling model is that when products are differentiated, the cost advantage does not lead to a market share increase at *full* strength. In other words, consumers’ relative preferences for different products, beyond a simple price comparison, causes frictions from a social efficiency perspective. These frictions in consumers’ switching prevents the low-cost producer from securing the socially efficient market share.

Let us first confirm this point in our model. Note that the social optimum requires marginal-cost pricing and hence $\tilde{p}_O = 0$ and $\tilde{p}_B = c$ in our model. With marginal-cost pricing, firm B’s socially optimal market share is computed as $\tilde{x}(c, 0) = \frac{t-c-\alpha}{2t}$. Under Assumption 5, firm B prefers price-matching and its market share is $x^m = \frac{t-\alpha}{2t}$. Hence, the socially optimal market share for firm B is less than firm B’s market share with price-matching when $\frac{t-c-\alpha}{2t} < \frac{t-\alpha}{2t}$, which holds for any $c > 0$. This means that price-matching itself does not fix the production inefficiency problem.

To find out whether price-matching mitigates or aggravates the distortion in production, we need to compare firm B’s market share with price-matching and its market share without price-matching. The comparison shows that the price-matching increases firm B’s market share even more if

$$x^m(p_B^m, p_O^m) > x^*(p_O^\alpha, p_B^\alpha) \iff \alpha > t - c. \quad (3.15)$$

Hence, price-matching exacerbates production inefficiency with $\alpha > t - c$. It implies that the product inefficiency problem can worsen even if the high-cost firm B has a

¹³See Lesson 3.4 on pg. 54 of Belleflame and Peitz (2015).

quality advantage ($\alpha < 0$). On the other hand, the price-match guarantee will reduce the distortion if $\alpha < t - c$, which requires that firm B's quality is better than firm O's by a sufficiently large margin.

Intuitively, the price-match guarantee dilutes the benefit of having a competitive advantage in relative cost. Consequently, the production inefficiency arises in a less restrictive environment under price-matching. Only when the high-cost firm's product shows a substantial quality superiority, the market split due to the price-match favors the societal outcome.¹⁴

Proposition 11. *Under Assumption 2, price-matching aggravates the production inefficiency problem when either the high-cost firm's quality is inferior to or not sufficiently superior to the low-cost firm's quality, i.e. $\alpha > t - c$.*

3.7 Discussion and conclusion

The scope of our paper is such that we do not consider certain other issues related to price-matching. First, we ignore the possibility of brick-and-mortars using price-matching to prevent the practice of “show-rooming”. Wu *et al.* (2015) and Mehra *et al.* (2017) address this issue. Second, the presence of “hassle costs” may limit the anti-competitive aspect of price-matching. If the burden of proving the existence of lower prices elsewhere falls on the buyer, this usually entails him a) searching for a lower price, b) bringing proof in the form of a flyer, printout or display of an advertisement on smartphone, etc., c) potentially filling out paperwork (some stores require registration) d) waiting for a store employee to process the claim, and so on. Even after incurring such costs, the buyer may not always get the price-match due to failing to comply with all the conditions or due to inconsistent implementation of such policies by store employees. Hviid and Shaffer, 1999 show that the presence of

¹⁴All the results in this section hold in the symmetric quality case also ($\alpha = 0$), albeit with simpler interpretations due to the absence of α .

even small hassle costs can diminish, if not eliminate, the collusive implications of price-match policies.

The caveat of the argument for hassle costs is that it holds when the burden of price-matching is mostly on the customer. If however firms undertake the responsibility of matching their rivals' prices and keep their posted prices equal to those of rivals, consumers face no hassle costs. Although we often observe both price dispersion and buyers bringing in rivals' advertisements to get price-matches, which is the criticism by Corts (1997) of non-hassle-costs based models of price-matching, there is a recent trend where the sellers are trying to minimize the hassle of price-matching. This may be because the sellers are becoming aware of how hassle costs limit the effectiveness of price-match guarantees. For instance, in 2014, Walmart announced a smartphone app that will search for lower prices elsewhere and issue refunds automatically as long as customers upload their Walmart receipts on to the app.¹⁵ This is more prevalent in the U.K. where Asda, Tesco and Sainsbury's offer similar price-match guarantees in which the burden of finding lower prices and refunding the buyer falls on the seller.

Price-matching as a price discrimination device is an alternative argument that seeks to explain why firms price-match (see Png and Hirshleifer (1987) and Corts, 1997 among others). When a price-matching firm has posted a price higher than the rivals' prices, only a small percentage of customers tend to exercise price-match guarantees. This is not surprising if hassle costs are high and the burden on obtaining the price-match is on the buyer. At the same time the potentially heterogeneous hassle costs play a role of self-selectively separating buyers into two types: high hassle-cost consumers who do not bother price-matching and low hassle-cost consumers who do. Hence, the firm manages to charge the regular high price to the high-type and the discounted price after price-matching to the low-type. Because in our model

¹⁵Source: "Walmart To Competitors: Catch Our Savings If You Can."
Retrieved from https://corporate.walmart.com/_news_/news-archive/2014/06/05/walmart-to-competitors-catch-our-savings-if-you-can

we consider the case where posted prices are already equal due to a price-match guarantee, studying the possibility of and implications for price discrimination is beyond the scope of your paper.

We also ignore the implications of price-match guarantees on consumer search. Price-match guarantees is likely to influence how long consumers keep searching for a lower price and also their reservation prices, which in turn can affect optimal pricing by firms. Two papers that study that are Janssen and Parakhonyak (2013) and Yankelevich and Vaughan (2016). Once again, equal posted prices in our model eliminate the need to analyze this aspect.

A literature on most-favored-customer (MFC) clauses¹⁶ as a collusion-facilitating device runs parallel to the one on price-matching and price-beating guarantees.¹⁷ In a two-period duopoly in which the firms choose prices simultaneously in each period, Cooper, 1986 shows that a firm has an unilateral incentive to offer a MFC clause to its customers. By combining a MFC clause with a higher than Bertrand-Nash non-cooperative price in the first period, it commits itself to that price in the second period. It acts like a price-leader since its first period price influences its rival's price in the second period. Similar to price-match guarantees, MFCs can lead to tacit collusion. While it may be interesting to see whether the results we get regarding distortion of investment incentives and production inefficiency also materialize with MFCs, they are not as common today as they were a few decades back and hence we do not pursue it here.

In this paper we illustrate three unintended effects of price-matching in a standard differentiated product duopoly market. Economists have studied various incentives for and effects of price-matching guarantees and similar business practices, but to our knowledge, the potential impact on investment incentives associated with price-

¹⁶Footnote 6 in Section 3.1.1 explains how most-favored-customer clauses are implemented.

¹⁷See Hviid and Shaffer (2010) for references. There are also some papers that consider both most-favored-customer and price-match clauses together, including Hviid and Shaffer (2010) and Holt and Scheffman (1987).

matching has not been given sufficient attention, and we try to fill the gap in this paper. Also, we illustrate how price-matching can aggravate the distortion of the high-cost firm producing too much relative to what is socially optimal.

Appendix: The simultaneous pricing game

Suppose that firm B did not choose to price-match. Then, generally we can think of an alternative version of price competition that the two firms compete with their simultaneous price choices. For this simultaneous pricing game, we use the hat symbol ($\hat{\cdot}$) for each variable to make them distinct from the variables in the sequential pricing game where we do not use the hat symbol.

The analysis when there was no price-match by firm B is straightforward. As usual, the analysis starts with characterizing the demand for each firm by identifying the indifferent consumer's location $\hat{x} = \frac{1}{2} + \frac{\hat{p}_O - \hat{p}_B}{2t}$, which gives the demand for B, $\hat{Q}_B(\hat{p}_B, \hat{p}_O) = \hat{x}$, and for O, $\hat{Q}_O(\hat{p}_B, \hat{p}_O) = 1 - \hat{x}$. Then, we set up each firm's profit maximization problem. For firm B, it is set up as $\max_{\hat{p}_B} \hat{\pi}_B = (\hat{p}_B - c)\hat{Q}_B$ and for firm O as $\max_{\hat{p}_O} \hat{\pi}_O = \hat{p}_O\hat{Q}_O$. Deriving the first-order necessary conditions for their prices, we obtain following two best responses: $\hat{p}_B(\hat{p}_O) = \frac{1}{2}(t + \hat{p}_O + c)$ and $\hat{p}_O(\hat{p}_B) = \frac{1}{2}(t + \hat{p}_B)$. Solving these two equations as a system, the prices in Nash equilibrium are derived as

$$\hat{p}_B^* = t + \frac{2}{3}c; \quad \hat{p}_O^* = t + \frac{1}{3}c. \quad (3.16)$$

where the asterisk at the subscript (*) signifies that we are considering the standard price competition without a price-match. Substituting (3.16) into $\hat{x}(\hat{p}_B, \hat{p}_O)$, the demands in equilibrium are derived as

$$\hat{Q}_B = \hat{x}^* = \frac{1}{2} - \frac{c}{6t}; \quad \hat{Q}_O = 1 - \hat{x}^* = \frac{1}{2} + \frac{c}{6t}. \quad (3.17)$$

As firm B's marginal cost is higher than that of firm O, the demand for firm B is

smaller than that of firm O. The demand gap $\frac{c}{3t}$ increases with c , but decreases with t . Using the derived prices and demands, the equilibrium profits are equal to

$$\hat{\pi}_B^* = (\hat{p}_B^* - c) \hat{x}^* = \frac{(3t - c)^2}{18t}; \quad \hat{\pi}_O^* = \hat{p}_O^* (1 - \hat{x}^*) = \frac{(3t + c)^2}{18t}. \quad (3.18)$$

For an interior solution $\hat{x}^* \in (0, 1)$, we need $c < 3t$ without which the market equilibrium is characterized by the so-called tipping equilibrium such that the online seller monopolizes the market. Intuitively, this corner solution arises when the cost disadvantage c is sufficiently large that firm B cannot survive as an effective competitor vis-à-vis the more efficient online rival. Aforementioned, we assume a full market coverage. The net surplus of the indifferent consumer must be non-negative, i.e. $v - t\hat{x}^* - \hat{p}_B^* \geq 0$ where v denotes the intrinsic value of a product. This condition leads to $v \geq \frac{3}{2}t + \frac{1}{2}c$. Intuitively, the market will be fully covered once the intrinsic value is large enough.

Now consider the other subgame ensuing from the brick-and-mortar firm's price-match commitment. Under the price-match announcement, one candidate for the equilibrium would be that the market will be evenly split as long as both firms are active and they charge the same price. In this case the marginal consumer is located at $\hat{x}^* = 1/2$ and both firms charge the price such that they extract the entire surplus from the marginal consumer:

$$\hat{p}_O^m = \hat{p}_B^m = v - \frac{t}{2}. \quad (3.19)$$

where the superscript m indicates that currently we consider the price-match. The non-negative price constraint requires $v \geq t/2$. With this equal price, both firms earn the profits of

$$\hat{\pi}_O^m = \frac{1}{2}(v - \frac{t}{2}); \quad \hat{\pi}_B^m = \frac{1}{2}(v - \frac{t}{2} - c) \quad (3.20)$$

where firm B will be active only if $v \geq t/2 + c$. Both of the constraints on price and no-exclusion of firm B at the matched price are subsumed by the full coverage assumption $v \geq \frac{3}{2}t + \frac{1}{2}c$.

However, before we can assert that (3.20) represent the price-match subgame payoffs, we need to check whether $\hat{p}_O^m = \hat{p}_B^m = v - \frac{t}{2}$ is sustained as an equilibrium pricing strategy. In fact, this is not an equilibrium. To see this point, consider firm B's deviation to $\hat{p}_B^d = v - t$. Then, consumers see no need to claim the price match because now $\hat{p}_O^d = v - \frac{t}{2} > \hat{p}_B^m = v - t$. Firm B's new payoff is $\hat{\pi}_B^d = v - t - c$ and this deviation strategy is profitable if

$$v - t - c > \frac{1}{2}(v - \frac{t}{2} - c),$$

that is, $v > c + \frac{3t}{2}$. This condition has no conflict with any restriction to the equilibrium and basically it boils down to v being sufficiently high, which is consistent with the full coverage assumption. This implies that there will be no equilibrium with simultaneous pricing such that both firms have a positive market share with the full market covered.

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